IDENTIFICATION OF FIRE SIGNATURES FOR SHIPBOARD MULTI-CRITERIA FIRE DETECTION SYSTEMS

~~SPECIFICATION~~

1.0 INTRODUCTION

The Navy program Damage Control-Automation for Reduced Manning (DC-ARM) is focused on enhancing automation of ship functions and damage control systems. A key element to this objective is the improvement of current fire detection systems. As in many applications, it is desired to increase detection sensitivity, decrease the detection time and increase the reliability of the detection system through improved nuisance alarm immunity. Improved reliability is needed such that fire detection systems can provide quick remote and automatic fire suppression capability. The use of multi-criteria based detection technology continues to offer the most promising means to achieve both improved sensitivity to real fires and reduced susceptibility to nuisance alarm sources [1]. An early warning fire detection system can be developed by properly processing the output from sensors that measure multiple signatures of a developing fire or from analyzing multiple aspects of a given sensor output (e.g., rate of rise as well as absolute value).

Although work has been done in the area of multi-signature detection, in many cases few sensor types have been examined (e.g., standard photoelectric smoke detectors and temperature or CO and CO_2 for gas signatures) and only singular standard test sources have been used. This work was aimed at developing a broad database of signatures from real fire and nuisance alarm sources particular to onboard situations. Using this database and data in the literature, multi-criteria alarm algorithms are being developed.

This report documents the FY 98-99 work including laboratory tests to identify signatures of realistic fire and nuisance alarm sources, review of typical fuel loadings and false alarm sources onboard USN ships and identification of potential discriminating alarm algorithm strategies. Based on the work performed to date, the report identifies the signatures that have the greatest potential value in an incipient fire detection system.

2.0 OBJECTIVE

The objective of this work was to determine the value of signatures from real fire and nuisance alarm sources as part of a multi-signature fire detection system. In addition, this work was aimed at identifying candidate signature combinations for potential prototype development.

3.0 APPROACH

The approach consisted of developing a broad database of signatures from real and nuisance alarm sources. This was accomplished through real-scale laboratory testing. Upon completion of the testing, various univariate and multivariate data analysis techniques were used with the database of signature measurements to identify candidate signature combinations for a multi-criteria fire alarm algorithm. Currently available smoke detection systems were considered as the benchmark for evaluating multi-signature detector performance. In addition to these efforts, a literature search and analysis was conducted of existing multi-signature fire detection technologies. This review of the state-of-the-art is presented in Reference [1].

The remainder of the report is divided into two main sections: 1) Experimental testing and 2) Data analysis. The section on experimental testing addresses the identification of applicable fire and nuisance sources onboard Navy ships, the experimental setup, test procedures and an overview of the tests conducted and results generated. The data analysis section discusses the methods used for data processing, the various univariate and multivariate data analysis techniques utilized and the results of the analyses.

4.0 EXPERIMENTAL TESTING

One hundred and twenty-six tests were included in the final database. These tests consisted of 26 different fire scenarios and 12 different nuisance sources. This section discusses the use of the specific fire and nuisance sources and the applicability to shipboard applications. The section also discusses the experimental setup, test procedures and an overview of the tests conducted and results generated.

4.1 Test Sources

Sources have been characterized as either, real alarm sources or nuisance alarm sources. Real alarm sources are undesired flaming or smoldering fires which if left unattended could result in personal injury and/or property damage. A fire detector should be able to detect this source and sound an alarm. A nuisance alarm source can be any source that causes a detector to sound an undesired alarm. Depending on the situation, a nuisance alarm may involve a controlled fire source, which is similar in character to other real fire sources. Tables 1a and 1b present the sources that were tested. A detailed description of each source is provided below with additional information on the test conditions summarized in Appendix A.

Incipient size sources were used in order to challenge the detection limits of the commercial smoke detectors and to establish the minimum detection capability of new multi-signature detection algorithms. A primary emphasis was placed on sizing the sources so that smoke levels and gas species concentrations increased slowly with respect to time. During previous work [2], it was observed that large sources can cause smoke detector measurements to

transition from near ambient conditions to alarm conditions in a matter of a few seconds (i.e., nearly a step function). This was particularly noticeable for sources that produced high levels of smoke very quickly, such that when the ceiling jet of smoke reached the detectors, all detectors and sensors responded sharply. When all sensors respond rapidly, it is difficult to identify differences in fire detection responses between single and multi-signature detection algorithms. Therefore, to develop the highest level of differentiation between response times of single and multi-signature detection algorithms, it was important to develop sources that transition over tens of seconds.

Table 1a. Summary of Real Fire and Nuisance Sources

Scenario No.	Source Description
1	Propane Burner
2	Heptane pool fire
3	JP-5 pool fire
4	JP-8 pool fire
5	Alcohol pool fire
6	Smoldering mattress
7	Flaming mattress (foam only)
8	Flaming mattress (loose bedding)
9	Flaming mattress (tucked bedding)
10	Smoldering pillow
11	Laundry pile fire
12	Smoldering electrical cable - LSDSGU-14: cross-linked polyolefin jacket, silicon rubber insulation
13	Smoldering electrical cable - LSTHOF-9: cross-linked polyolefin jacket, ethylene propylene rubber insulation
14	Smoldering electrical cable - LSTPNW-1 ½: cross-linked polyolefin jacket, cross-linked polyethylene insulation
15	Flaming electrical cable - LSDSGU-14: cross-linked polyolefin jacket, silicon rubber insulation
16	Flaming electrical cable - LSTHOF-9: cross-linked polyolefin jacket, ethylene propylene rubber insulation
17	Flaming electrical cable - LSDSGU-50: cross-linked polyolefin jacket, silicon glass insulation
18	Office Trash Can fire
18	Pipe insulation (NH Armaflex) fire
20	Pipe insulation coated with oil fire (NH Armaflex)
21	Pipe insulation (Calcium silicate) fire
22	Pipe insulation coated with oil fire (Calcium silicate)
23	Polyimide acoustic insulation
24	Nomex honeycomb wall panel (TODCO)
25	Nomex honeycomb wall panel (Hexcel)
26	Polyimide acoustic insulation without perforated face material

Table 1b. Summary of Real Fire and Nuisance Sources

Scenario No.	Source Description
1	Burning toast
2	Normal toasting
3	Welding
4	Cutting steel with acetylene torch
5	Grinding steel
6	Grinding cinder block
7	Cutting lauan board
8	Burning popcorn in microwave
9	Gasoline engine exhaust
10	Electric heater and halogen lamps
11	People
12	Cigarette smokers

The heights of each source above the floor were selected to be representative of actual conditions onboard ship and to facilitate the objectives discussed above. Table 2 shows the typical heights of each deck on the DDG 67 [Compartment, Access and Deck Plans Feb. 1996]. As can be seen, most spaces are 2.44 m (8 ft) high. Therefore, a height of 2.44 m was considered the standard height in developing the test scenarios.

Table 2. Typical Heights of Each Deck on the DDG 67

Deck	Room Description	Height m (ft)
05	Dir. Eqpt. Room 1	1.8 (6)
04	Chart room, Plot Hs.	2.4 (8)
03	Radar Room	3.5 (11.5)
02	Stateroom	2.4 (8)
01	Technical library	2.4 (8)
Main	Mess room, Damage Control Central	2.3 (7.5)
Second	Crew living space	2.4 (8)
Third	Living space, Engine room	2.4 (8)
Fourth	Machine room	2.7 (9)

4.2 Real Fire Alarm Sources

4.2.1 Scenario 1 - Propane Burners

A propane fueled Meker burner (Fisher, cat. no. 03-902P) and a propane fueled bunsen burner (Fisher, cat. no. 03-962P) with a wing tip (Fisher, cat. no. 03-995B) were used as the initiating sources for several fire scenarios. Without an external heat source, several of the fuel

sources would not burn. Therefore, the propane burner was used with a minimal flame size to involve the fuel source, while trying to minimize the impact on the sensors from the propane flame emissions. In order to assess the impact of the propane burner, a number of tests were conducted with several variations to determine whether the propane burner would significantly affect the sensors compared to the fuel sources of interest. As will be seen below, the propane burner did not cause either the conventional photoelectric or ionization detector to alarm even at very sensitive alarm settings. The propane burner tests were conducted 1.5 m (5 ft) below the ceiling.

Although the propane burner is not considered a primary fire source for shipboard applications, the source is included as a fire scenario in the database for completeness and as a means to evaluate the detection limits of multi-criteria alarm algorithms. In other words, could the alarm algorithms detect these very small fires even though conventional smoke detectors could not?

4.2.2 Scenario 2 - Heptane Pool Fire

A pool fire was produced by burning 100 ml of heptane in a 7.7 x 7.7 x 2.2 cm high (3 x 3 x 0.87 in.) square, steel pan. The majority of tests were conducted with the source 1.5 m (5 ft) below the ceiling. Tests DCAS053 and DCAS145 were conducted with the source 2.4 m (8 ft) from the ceiling. The pool fire was ignited with a match or a butane lighter. Heptane is a typical hydrocarbon fuel which has been used in past studies and is used in standardized tests.

4.2.3 Scenario 3 - JP-5 Pool Fire

A pool fire was produced by burning 25 ml of JP-5 fuel in a 7.7 x 7.7 x 2.2 cm high (3 x 3 x 0.87 in.) square, steel pan positioned 1.5 m (5 ft) below the ceiling. The first test (DCAS027) was conducted with 50 ml of fuel, which was later determined to unnecessarily extend the burning duration. The JP-5 fuel was obtained from Navy stock (density of 791 kg/m^3 and a flash point of 62°C (144°F)). The pool fire was ignited with a standard propane torch.

4.2.4 Scenario 4 - JP-8 Pool Fire

A pool fire was produced by burning 25 ml of JP-8 fuel (MIL T83133D) in a 7.7 x 7.7 x 2.2 cm high (3 x 3 x 0.87 in.) square, steel pan positioned 1.5 m (5 ft) below the ceiling. The JP-8 fuel was obtained from Navy stock (density of 807 kg/m^3 and a flash point of 52°C (126°F)). The pool fire was ignited with a standard propane torch.

4.2.5 Scenario 5 - Alcohol Fire

Three of the four alcohol pool fires were produced by burning 100 or 150 ml of 70% aqueous isopropyl alcohol in a 12.5 x 12.5 x 2.2 cm high (4.9 x 4.9 x 0.87 in.) square, steel pan positioned 1.5 m (5 ft) below the ceiling. One test was conducted with 50 ml of alcohol in a 7.7 x 7.7 x 2.2 cm high (3 x 3 x 0.87 in.) square, steel pan. The pool fire was ignited with a standard propane torch. Alcohol represents a fuel which produces very little visible combustion products

and presents a challenging fire for smoke detectors, particularly photoelectric or sensors that detect visible particulate. Alcohol and alcohol-based products are also used as cleaning products and may be involved in shipboard fires.

4.2.6 Scenario 6 - Smoldering Mattress and Bedding

A Navy mattress (MIL-M-18351F(SH)) consisting of a 11.4 cm (4.5 in.) thick Safeguard polychloroprene foam core covered with a fire retardant cotton ticking was outfitted with the following items:

- Two sheets - Federal Specification DDD-S-281,
- One bed spread - Federal Specification DDD-B-151, and
- One blanket - Federal Specification MIL-B-844.

The composite fuel source was cut into 15 x 15 cm (6 x 6 in.) squares.

The smoldering fire source consisted of placing one square sample 1.5 m (5 ft) below the ceiling and resting a 300 W rated heating coil (Eagle, heating coil 415-120 V, 3.3 cm (1.3 in.) diameter, 6.9 cm (2.75 in.) long) on the center of the top blanket. The heating coil was energized to 54 V. The bedding materials were layed flat on one another on top of the mattress sample. The heating coil was allowed to rest on the sample under its own weight. The exposed surface area of sample to the heating coil was approximately 19 cm^2 (2.9 $in.^2$). The power to the heating coil was turned on after the initial background data was collected, and remained on throughout the test.

4.2.7 Scenario 7 - Flaming Mattress Foam

A sample of mattress foam (Safeguard polychloroprene) without ticking material (i.e., the cloth around the foam) was exposed to a 13 cm (5 in.) long, horizontal propane flame from the Meker burner with wing tip located 13 cm (5 in.) from the sample. The flame impinged on the side of the foam sample, and the source was 1.5 m (5 ft) below the ceiling. The foam did not sustain flaming combustion.

4.2.8 Scenario 8 - Flaming mattress (loose bedding)

The same mattress and bedding sample as described in Scenario 6 was used in this scenario. The sample was positioned 1.5 m (5 ft) below the ceiling. In these tests, the bedding material (sheets, blanket and bed spread) was allowed to loosely drape on one side of the foam mattress. For two of the four tests (DCAS010 and DCAS013), a propane Meker burner with a 13 cm (5 in.) long flame was positioned horizontally 13 cm (5 in.) away from the side of the sample. The flame impinged on the bedding material approximately 2 cm (0.8 in.) above the bottom edge. For the other two tests (DCAS039 and DCAS040), a horizontal propane bunsen burner with a wing tip exposed the draped bedding material to a 8 cm (3 in.) long flat flame positioned 1.5 cm (0.6 in.) from the source.

4.2.9 Scenario 9 - Flaming mattress (tucked bedding)

The same mattress and bedding sample as described in Scenario 6 was used in this scenario. In these tests, the bedding material was wrapped around the mattress sample and tucked underneath so that the materials were tightly held against the mattress. This arrangement represented a prepared bed. For two of the three tests (DCAS066 and DCAS067), a horizontally oriented propane bunsen burner with a wing tip exposed the bedding material to a 8 cm (3 in.) long flat flame positioned 1 cm (0.4 in.) from the mattress. The flame directly impinged on the side of the sample. For the third test (DCAS068) the propane flame was reduced in size to 2.5 cm (1 in.) long and was positioned 1 cm (0.4 in.) from the sample.

4.2.10 Scenario 10 - Smoldering Pillow

A Navy feather pillow (Federal Specification V-P-356, Type 4) and a pillow case (Federal Specification DDD-P-351) were cut and stapled into smaller samples measuring approximately 22 cm by 34 cm (9 by 13 in.) for all tests, except Test DCAS048 which consisted of a 15 cm by 15 cm (6 by 6 in.) sample. The ignition source for all tests was a 300 W rated heating coil (Eagle, heating coil 415-120 V) energized to 54 V (i.e., approximately half power). Four tests were conducted with variations in each test as follows:

Test DCAS048 - the 15 x 15 cm (6 x 6 in.) sample was ignited 1.5 m (5 ft) below the ceiling by placing the heating coil on the top center of the sample under its own weight. The exposed surface area of sample to the heating coil was approximately 19 cm^2 (2.9 $in.^2$). The power to the heating coil was turned on after the initial background data was collected.

Test DCAS049 - the 22 cm x 34 cm (9 x 13 in.) sample was ignited 1.5 m (5 ft) below the ceiling by placing the heating coil on the top center of the sample under its own weight. The exposed surface area of sample to the heating coil was approximately 19 cm^2 (2.9 $in.^2$). The power to the heating coil was turned on after the initial background data were collected. The only difference between Tests DCAS048 and DCAS049 was the size of the pillow sample and the addition of a pillow case in Test DCAS049.

Test DCAS050 - This test was different from Test DCAS049 and DCAS048 in the location of the pillow and the position of the ignition source. In Test DCAS050, the pillow was positioned 0.6 m (1.9 ft) from the end wall, rather than 1 m (3.3 ft) and the heating coil was positioned beneath the center of the pillow, rather than on top.

Test DCAS055 - In this test, the pillow was positioned 1 m (3.3 ft) from the end wall (same as Test DCAS048 and DCAS049) and 1.5 m (5 ft) below the ceiling (same as Test DCAS050). The sample was ignited 1.5 m (5 ft) below the ceiling by placing the heating coil on the corner of the sample. The exposed surface area of sample to the heating coil was approximately 19 cm^2 (2.9 $in.^2$).

4.2.11 Scenario 11 - Laundry Pile Fire

A simulated laundry fire was created by igniting a small pile of towels and clothing that could be found onboard ship. The pile consisted of one white, 100% cotton terry towel (FED SPEC DDD-T-551), a 100% cotton T-shirt (size large), a 55/45 cotton/polyester pair of boxers and a pair of mens 100% cotton briefs with elastic waist band. The items were randomly piled in a small heap on top of a fire retardant board. The pile was located 2.4 m (8 ft) below the ceiling. The first test (DCAS018) was ignited using the Meker burner with the wing tip impinging horizontally on the edge of the pile. This fire grew rapidly. In order to slow the fire growth, the other two tests (DCAS054 and DCAS057) were ignited using a butane lighter randomly applied to the waistband of the cotton briefs for 20 seconds.

4.2.12 Scenario 12 to 17 - Smoldering Electrical Cable and Flaming Electrical Cable

Various types of electrical cables used onboard ship were ohmically heated and ignited. All wires used onboard ship have crosslinked polyolefin jackets (XLPOLYO) which is considered a low smoke cable material (all cables meet MIL-C-24643). Four different insulation materials are used; ethylene propylene rubber (EPR), silicon rubber, silicon glass and crosslinked polyethylene (XLPE). The four cables tested are listed in Table 3 along with the details of the test setup. In general, an approximately 33 cm (13 in.) length of cable (or bundle of cables) was horizontally connected between two rigid copper buses (6 mm by 25 mm (0.25 by 1 in.) stock) which were connected to a 600A arc welder (Miller 452 with 4/0 600 V copper cables). The supply current to the cable sample was measured using a clamp on ammeter (Amprobe, model ACDC-600A) and confirmed via an ammeter on the welder. After initial background data was collected, current was supplied to the cable sample and ramped from zero to the initial set point (as indicated in Appendix A, ranged from 250 to 600A) over a period of approximately 30 seconds. For the smoldering cable tests, the cables remained energized until the end of the test. In some cases, the current supply level to the cables was changed and is detailed in Appendix A.

Table 3. Details of Electrical Cable Tests

Sample No.	Cable Type[a]	Military Part No. M24643/	Conductor Size AWG	No. of cables per test sample bundle	No. of conductors per cable	No. of Conductors Energized
1	LSTHOF-9	3-27UN	9	6[b]	3	1
2	LSDSGU-14	15-04UN	9	6[b]	2	1
3	LSDSGU-50	15-06UN	3	1	2	1
4	LSTPNW-1 1/2	52-01UN	22	10[c]	3	30

a. All cables manufactured by Monroe Cable Co., a supplier for the DDG 78.
- LSTHOF-9: crosslinked polyolefin jacket, ethylene propylene rubber insulation
- LSDSGU-14: crosslinked polyolefin jacket, silicon rubber insulation
- LSDSGU-50: crosslinked polyolefin jacket, silicon glass insulation
- LSTPNW-1 1/2: crosslinked polyolefin jacket, crosslinked polyethylene insulation

b. Center cable 33 cm (13 in.) long with 6 cm (2.5 in.) of insulation stripped from each end. Other cables were 20 cm long and bundled around center cable and held in place with 18 gauge wire wrapped around each end of the bundle.

c. All cables 33 cm (13 in.) long with 6 cm (2.5 in.) of insulation stripped from each end.

For the flaming cable tests, once the heated cable started to smolder and release visible smoke, a propane torch was initially applied to the bottom center of the sample and then moved to the end if ignition did not occur at the center. Ignition only occurred at the center of the LSTPNW-1 ½ cable test.

4.2.13 Scenario 18 - Office Trash Can

A trash can fire was created to simulate a possible fire in an office space. The trash can fire consisted of placing 10 crumpled brown paper towels, 10 crumpled sheets of standard white copier paper (216 mm x 279 mm (8.5 x 11 in.), 75 g/m^2), 5 flats sheet of white copier paper into approximately 6 L (1.6 gal) metal trash can lined with a clear plastic trash bag (8 micron (0.31 mil) thick). The cylindrical can was 0.33 m (13 in.) high, tapering from 0.34 m (13.5 in.) diameter at the top to 0.25 m (10 in.) at the bottom. The paper was randomly thrown into the can. The first test fire (DCAS058) was started by tossing a lit wooden stick match into the can. This fire grew rapidly and saturated the ion smoke detector within 45 seconds with a step change in response. The second test (DCAS059) fire consisted of tossing a lit cigarette into the trash can. The cigarette burned out after 10 minutes. During this time there was no visible smoke or fire other than that produced by the cigarette. The paper was not involved. At this time a heating coil at 55 V was placed into the can and ignition occurred after the supply voltage was increased to 94 V. The last three tests (DCAS060-DCAS062) were ignited initially with the heating coil at 94 V inserted near the center of the trash can in contact with the paper. In all tests, the trash can was set on a platform 2.4 m (8 ft) below the ceiling.

4.2.14 Scenario 19 to 22 - Pipe Insulation

Pipe insulation materials as used onboard the DDG51 class ships were exposed to flame. These insulation materials are widely found onboard the ship. Although they are not highly combustible or likely to be the initial source of a fire, their widespread use makes it possible to have these materials involved at the source of a fire. Therefore, these materials were exposed to a flame in order to measure their contribution to potential incipient fire signatures. Two different samples of pipe insulation were used as sources: 1) Calcium silicate insulation with glass cloth lagging, and 2) Non-halogenated (NH) elastomeric foam (Armaflex) with rewettable glass lagging. All materials were obtained from Reilly Benton Insulation Co., a Navy supplier. The calcium silicate sample (MIL-I-278) was 5.1 cm (2 in.) internal pipe size and 2.54 cm (1 in.) thick. The glass lagging cloth (MIL-C-20075, Ty CL 3, Reilly Benton Type 300) was applied to the calcium silicate with MIL-A-3316 Class I Grade A adhesive (Vimasco 713). The NH Armaflex foam was 7.62 cm (3 in.) internal pipe size and 1.27 cm (0.5 in.) thick. The Armaflex foam was covered with rewettable glass lagging (MIL-C-20079 obtained from Reilly Benton).

Samples of insulation were cut in 45 cm (18 in.) long samples and mounted in a vertical position around PVC pipe with corresponding diameters. The lagging was then applied around the insulation per manufacturers instruction. After assembly, samples were painted with chlorinated Alkyd White, DOD-E-24607, Color 27880.

In all tests, the vertical pipe assembly sample was exposed on its side (at 2 cm (0.8 in.) above base) to a bunsen burner with a wing tip and a 2.5 cm (1 in.) long flame. Half of the tests exposed the flame to the insulation assembly as described above. The other half of the tests consisted of coating the lagging with lubricating oil (2190-TEP, MIL-L-17331 H(SH), from Navy stock). The addition of oil was investigated because this condition has been found to exist on ships. The sources were set on a platform 1.5 m (5 ft) below the ceiling.

4.2.15 <u>Scenario 23 and 26 - Polyimide Acoustic Insulation</u>

Polyimide acoustic insulation is used on interior surfaces of the ship and is a material that could be involved in an incipient fire. The material used was 5.1 cm (2 in.) thick, perforated face polyimide acoustic board, DOD-I-24688, Type II, Class 2. The materials were obtained from Imi-Tech Corporation and assembled by Reilly Benton. Vertical samples 30 cm (12 in.) high were exposed to a 13 cm (5 in.) flame from a horizontal Meker burner with a wing tip. The horizontal burner impinged a flame on the sample (2 cm (0.8 in.) above base) perpendicular to the surface.

One test (DCAS065) was conducted with the perforated face material removed. In this test, the sample was exposed to a 2.5 cm (1 in.) flame from a bunsen burner with a wing tip positioned 1 cm (0.4 in.) from the surface.

4.2.16 <u>Scenario 24 and 25 - Nomex Honeycomb Wall Panel</u>

Nomex honeycomb wall panels are used on interior surfaces of the ship and constitute material that could be involved in an incipient fire. The Nomex panels were non-filled honeycomb with phenolic resin impregnated fiberglass facing over the aramid fiber honeycomb core. The honeycomb was 0.6 cm (0.25 in.) hexagonal MIL SPEC MIL-C-81986, with a density of 48 kg/m^3 (3 lb/ft^3). The overall panel thickness was 1.6 cm (+0.000 cm, - 0.08 cm) (0.625 in. ((+0.000 in., -0.030 in.)) thick including the decorative face sheets. The decorative face sheets were high pressure laminate (HPPL) in accordance with MIL SPEC MIL-P-17171, Type IV except that they were 0.07 cm - 0.09 cm (0.027 - 0.037 in.) thick. The HPPL was bonded directly to the fiberglass face sheet using the phenolic resin system per MIL SPEC MIL-R-9299, Grade A. The panels were obtained from two sources:

- TODCO Engineering Products (*WHITE*)- These panels meet the above listed specifications, and

- Hexcel Corporation (*YELLOW*)- These panels met the specifications as described above with one exception. Hexcel's panel was not qualified to MIL-C-81986 because it failed a Beam Flexure test. The NAVSEA specifications require a strength of 96.5 x 10^6 Pa (14,000 psi) and the panel's strength was 93.1 x 10^6 Pa (13,500 psi).

Vertical samples 30 cm (12 in.) high and 10 cm (4 in.) wide were exposed to either a flame from a Meker burner or bunsen burner with wing tips (see Appendix A). The horizontal burner impinged a flame on the sample perpendicular to the surface. The source was on a platform 1.5 m (5 ft) below the ceiling.

4.3 Nuisance Alarm Sources

4.3.1 Scenario 1 - Burning Toast

One slice of white bread was placed in a four-slice toaster (Toastmaster Model D1050) located 1.5 m (5 ft) below the ceiling. The toaster lever was set to "dark," and the lever was clamped down to allow continual heating and burning of the toast. The toaster was unplugged at 7 minutes after it was turned on to prevent damage to the toaster. At this time, the smoke level in the room was quite dense and sufficient to cause an alarm. This event represents a cooking event that can occur in a pantry or galley. Cooking events have not been identified as a large source for nuisance alarms onboard ship. However, there is little documented information characterizing shipboard detection systems performance. The inclusion of several cooking events was deemed appropriate since cooking events are the leading causes of nuisance alarms with residential detectors, which work on the same principles of operation as conventional smoke detectors would be used onboard ship.

4.3.2 Scenario 2 - Normal Toasting

Eight slices of white bread were placed in two, four-slice toasters (Toastmaster Model D1050). The toaster lever was set to "dark." Once the toast was done and the toaster automatically stopped, new bread was inserted in the toaster and the procedure repeated. Up to 24 slices of bread were toasted during a test. The toasters were located 1.5 m (5 ft) below the ceiling.

4.3.3 Scenario 3 - Welding

Welding and other hot work are typical maintenance activities that can occur onboard a ship. Welding of steel was conducted in the compartment 2.4 m (8 ft) below the ceiling. The arc welding consisted of running a weld across a 0.32 or 0.48 cm (0.125 or 0.189 in.) thick steel plate using a 0.32 cm (0.125 in.) Number 7018 rod and a constant current setting of 200A. The welder was a Miller 452 CC. Welding continued over a 7 to 10 minute period stopping only to change rods.

4.3.4 Scenario 4 - Cutting Steel with Acetylene Torch

An oxy-acetylene torch was used to cut 0.32 cm (0.125 in.) thick steel, 2.4 m (8 ft) below the ceiling. Cutting occurred in a continuous fashion by cutting off 30 cm (12 in.) long strips of steel from the plate.

4.3.5 Scenario 5 and 6 - Grinding Steel and Grinding Cinder Block

The objective of the grinding tests was to generate particulate matter that may be representative of either dirty work environments or conditions arising from maintenance activities. A standard 11.4 cm (4.5 in.) sander/grinder was used with a 11.4 cm (4.5 in.) metal disk (Norton #75922) to grind either steel plate or cinder block 2.4 (8 ft) below the ceiling. Grinding was performed on a continuous basis for approximately 10 minutes.

4.3.6 Scenario 7 - Cutting Luaun Board

Cutting of luaun board was another activity to generate particulate that may cause nuisance alarms with detectors. A circular saw was used to cut sheets of 0.32 cm (0.125 in.) thick luaun board 2.4 m (8 ft) below the ceiling. For the tests conducted, cutting times ranged from 3.5 to 9 minutes.

4.3.7 Scenario 8 - Burning Popcorn in Microwave

Burning popcorn in a microwave is a plausible event that may occur in a pantry. This source consisted of heating a standard popcorn pack in a 1500 W microwave oven set to high for 12 minutes. At the completion of the test the popcorn was burned and the package was charred. The charring of the package was more significant on the side in contact with the microwave. The microwave was on a platform 1.5 m (5 ft) below the ceiling.

4.3.8 Scenario 9 - Gasoline Engine Exhaust

A 18 hp gasoline engine (part of a gas-powered power washer) was operated inside the test compartment at floor level for approximately fifteen minutes. This source was conducted to simulate a possible event of exposing detectors to exhaust gases that are inadvertently drawn into the ship.

4.3.9 Scenario 10 - Electric Heater and Halogen Lamps

If a multi-signature fire detector were to use a temperature sensor, a temperature rise in a space from non-fire sources would constitute a potential nuisance alarm event. The use of electric heaters and worklights were a means to produce realistic temperature rises in a compartment which could occur from the same such equipment or the start up of other electrical devices that generate heat. The equipment used in these tests consisted of one or two 1400 W electric heaters (Rival Model No. RT12/1) set to the maximum heating level and one 500 W halogen work light (Regent). The first test (DCAS133) used only one electric heater. Three other tests (DCAS134-DCAS136) were conducted using all three heat sources. The sources were positioned 1.5 m (5 ft) below the ceiling, 3 m (10 ft) from the end wall (i.e., 1 m (3.3 ft) from the sensors).

4.3.10 Scenario 11 - People

People within the test compartment was included as a potential nuisance source since gas species such as carbon dioxide and oxygen can change in a space due to the presence of people. Carbon dioxide (CO_2) concentrations can increase in a meeting room up to 2000 ppm. Consequently, a multi-signature fire detector using a CO_2 sensor may be prone to false alarms where people are present. These tests consisted of 4 or 5 people randomly walking and talking in the closed room below the area where the sensors were mounted.

4.3.11 Scenario 12 - Cigarette Smoke

Although smoking is prohibited inside Navy ships, it still remains a very plausible nuisance source. The cigarette smoke test consisted of one to four people chain smoking cigarettes (Parliament Lights) within the compartment. The people were allowed to wander around in the general area below the sensors. During the six tests conducted, 6 to 14 cigarettes were smoked in the closed compartment over time periods of 8 to 15 minutes.

4.4 Experimental Setup

Figure 1 shows a schematic of the test compartment and the general placement of the fire/nuisance alarm source and the sensors. The overall dimensions of the compartment were 4.1 x 6.5 m x 3.6 m high (96 m^3). The majority of the sources were centered 1 m (3.3 ft) away from the end wall. The sensors were positioned on an arc 4 m away from the primary source location. The sensors were also attached to the underside of a 2.44 m x 0.59 m board which was suspended 0.3 m below the compartment ceiling. The sensors were not mounted directly to the ceiling in order to prevent sensors from being in the direct path of the ceiling jet of smoke, gases or other particles originating from the source. This arrangement further assures that all sensors were being exposed to the same uniform mixture. In addition, the 0.3 m position below the ceiling is representative of the typical smoke/heat detector placements on the underside of beams.

Table 4 presents a list of the instruments used in the test program. Under the column labeled species, the parenthetical term represents the sensor name used throughout this program. The majority of the gas sensors were electrochemical cell technology, except as noted below. These sensors were used because they provided a means to economically measure many species. Past experience with the carbon monoxide (CO) sensors indicated that these sensors are accurate at low ppm concentrations, are easy to operate and calibrate and are reliable over repetitive testing. The general hydrocarbon sensor (calibrated with ethylene) was a solid state metal oxide sensor. The carbon dioxide (CO_2) meter was one designed for indoor air quality measurements based on non-dispersive infrared (NDIR) technology. All of the gas sensors operated via gas diffusion to the unit.

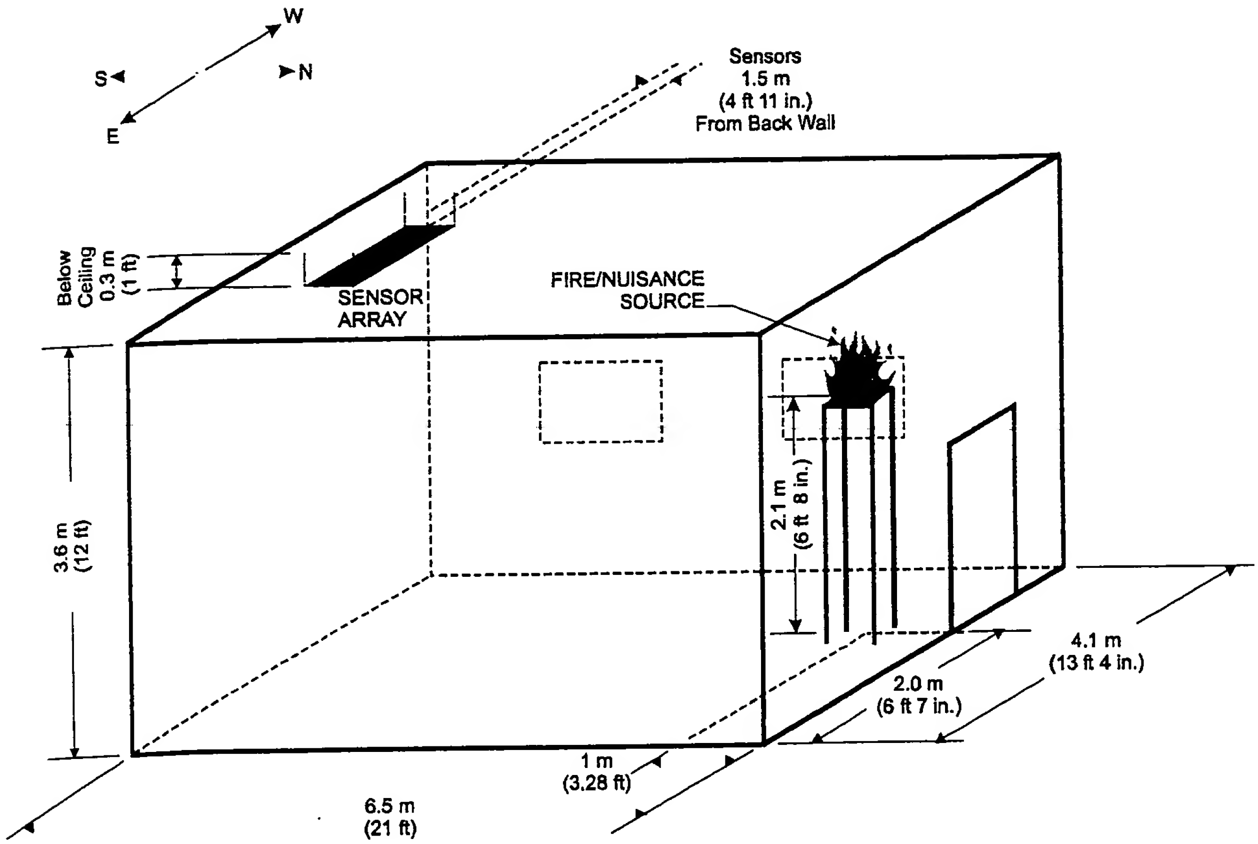

Fig. 1 – Schematic of test compartment

Table 4. Instrumentation for Multi-criteria Detection Tests

No.	Species	Sensor Range	Resolution	Instrument Model No.	Manufacturer
1	Oxygen (O_2)	0-25%	0.1% O_2	6C	City Technology
2	Carbon monoxide w/ H_2 compensation ($CO_{4000\ ppm}$)	0-4000 ppm	1 ppm	A3ME/F	City Technology
3	Carbon monoxide ($CO_{50\ ppm}$)	0-50 ppm	0.5 ppm	TB7E-1A	City Technology
4	Carbon dioxide (CO_2)	0-5000 ppm	accuracy= greater of $\pm$5% of reading or $\pm$100 ppm	2001V	Telaire/Englehard
5	C_1 to C_6 Hydrocarbons (Ethylene)	0-50 ppm ethylene (C_2H_4)	$\pm$2.5 ppm	SM95-S2 with general hydrocarbons solid state sensor	International Sensor Technology
6	Hydrogen (H_2)	0-200 ppm	2 ppm	TE1G-1A	City Technology
7	Hydrogen chloride (HCL)	0-10 ppm	0.5 ppm	TL1B-1A	City Technology
8	Hydrogen cyanide (HCN)	0-25 ppm	0.1 ppm $\pm$2% F.S. accuracy	4664-40-1-1-1	EIT
9	Hydrogen sulfide (H_2S)	0-5 ppm	0.1 ppm	TC4A-1A	City Technology
10	Sulphur dioxide (SO_2)	0-10 ppm	0.5 ppm	TD2B-1A	City Technology
11	Nitric oxide (NO)	0-20 ppm	0.5 ppm	TF3C-1A	City Technology
12	Nitrogen dioxide (NO_2)	0-5 ppm	0.1 ppm	TG3A-1A	City Technology
13	Temperature (Thermocouple or TC)	-200 to 1250°C	1°C or 0.75%	Type K, 0.127 mm bare bead TC	Omega
14	Temperature (Temp Omega)	-20°C to 75°C	$\pm$0.6°C accuracy	HX93 transmitter (RTD)	Omega
15	Relative humidity (RH)	3-95%	$\pm$2% RH accuracy	HX93 transmitter	Omega
16	Photoelectric smoke detector (Photo)	0 - 19% Obs/m		4098-9701	Simplex
17	Ionization smoke detector (ION)	1.6 -10% Obs/m		4098-9716	Simplex
18	Residential ionization smoke detector (RION)			83R	First Alert
19	Optical Density Meter (ODM) Laser and photodiode with 0.965 m spacing			VDM-2 670 nm, 2 mW laser MRD 500 PIN silicon Photodiode	Meredith Motorola
20	Measuring Ionization Chamber (MICX, MICY, MICY20)			EC-912	Delta Electronics Testing

Table 4. Instrumentation for Multi-criteria Detection Tests (Continued)

No.	Species	Sensor Range	Resolution	Instrument Model No.	Manufacturer
21	UL 217 Photocell-lamp assembly for optical density (UL217 Photo)			Type 4515 spot light at 2.4 v	Grainger
	1.55 m (61 in.) spacing			Weston 856-RR Photovoltaic Cell	Huygen Corp.

Multiple technologies and devices were used to obtain smoke measurements. The benchmark measurements consisted of conventional, commercial photoelectric and ionization smoke detectors. The Simplex ionization detector (Model 4098-9716) and the Simplex photoelectric detector (Model 4098-9701) were supplied with a specially designed hardware/software package which polled the detectors every 4 to 5 seconds and saved the data to a computer file. Simplex provided experimental data from which the detector outputs were correlated to percent obscuration measurements. In addition to the commercial smoke detectors, a residential ionization smoke detector (First Alert 83R) was also included. The residential ionization detector was a standard battery operated single station unit that was modified to provide an analog voltage output to the main data acquisition system. Although a direct correlation to percent obscuration was not available for the residential ionization detector, the signal provided a secondary means of measuring the change in smoke density.

Besides the ionization smoke detectors, a measuring ionization chamber (MIC) was used to measure smoke. The EC-912 MIC is the internationally recognized standard as the reference ionization chamber and is used in UL 217 [3] and 268 [4] for evaluating ionization smoke detectors. This unit operated by drawing a gas sample through the MIC via a pump located outside of the test compartment. The MIC was located on the sensor mounting board such that the sample flow did not effect other sensors. Appendix B contains information on the sensor theory of operation and output from the MIC. The MIC yielded three output values identified as MICX, MICY and MICY20 (see Appendix B). MICX is representative of the smoke density ranging from 0 to 1 when the smoke density is infinite. MICY and MICY20 are different expressions of the same output signal.

Two different apparatus were used to measure the optical density in the test compartment. The first measurement consisted of a 670 nm laser and photodiode arrangement spaced 0.97 m (3.2 ft) apart. The second setup consisted of a visible light and photocell arrangement specified in UL 217 and 268. The UL 217 setup was only used in Tests DCAS053-145. For both instruments, smoke/particulate levels were reported as percent obscuration per meter using the following equation [4]:

$$\%\ Obs/m = [1-(\frac{I}{I_o})^{\frac{1}{d}}]100 \tag{1}$$

where I is intensity of the transmitted light under test conditions, I_o is the intensity of the transmitted light under normal ambient conditions, and d is the distance between the light source and the receiving instrument.

Except for the Simplex detectors (which were recorded on a separate computer), the data acquisition consisted of a 12-bit analog/digital I/O board (Keithley Metrabyte DAS-1602) with EXP-1600 multiplexer and signal conditioning boards. The output of the instrumentation was recorded on a personal computer using Labtech Notebook software (version 9.01). Outputs from all instruments, except for the ionization and photoelectric detector, were recorded every second. The conventional smoke detectors were logged every 4 to 5 seconds, as dictated by the UL Tester program.

4.5 Test Procedures

Prior to starting the test, the compartment was closed (i.e., vent damper closed and door closed). During the exposure of the sensors to the source, there was no ventilation in the test compartment. The general test procedure was to collect a minimum of 60 seconds of background data before the sources were initiated. After initiating the source, the test continued until the source was consumed, all smoke detectors alarmed, or steady-state conditions were achieved. At this time the source was secured and the compartment was ventilated. For the majority of tests, the data acquisition systems continued to record sensor data until the conditions in the test compartment were back to ambient levels.

4.6 Results

A summary of all valid tests included in the database is presented in Table 5 in chronological order. Table 6 presents the same data arranged by test scenario as designated in Table 1. Table 5 and 6 include the test number, scenario type (real or nuisance), source description and relevant times. The times include the test time at which the source was ignited/started, the test time at which the flame was out or the source was stopped and the response times of the photoelectric and ionization smoke detectors at three different alarm sensitivities (Section 5.1 discusses the details of the data processing). The response times represent the times from ignition/start of the source to the time the conventional smoke detector reached the specified alarm threshold value. The first setting for each detector type corresponded to the typical alarm threshold of conventional detectors: 4.2% Obs./m (1.3% Obs./ft) for ionization detectors and 11.0% Obs./m (3.5% Obs/ft) for photoelectric detectors [5]. The second setting was the minimum alarm level allowed by UL Standard 268 (1.63% Obs./m (0.5% Obs./ft)), and the third setting was half the value of the minimum alarm setting (9.82% Obs./m (0.25% Obs/ft)). The third setting of 0.82% Obs/m corresponds to a very sensitive smoke detection.

Table 5. Summary of Tests Conducted and Response Times of Photoelectric and Ionization Smoke Detectors

Test ID	Scenario Type and No. (Real/Nuisance)	Source Description	Comments	Ignition/Start Time (seconds)	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec) 11 % obscuration per meter	Photoelectric Alarm Times (sec) 1.63 % obscuration per meter	Photoelectric Alarm Times (sec) 0.82 % obscuration per meter	Ionization Alarm Times (sec) 4.2 % obscuration per meter	Ionization Alarm Times (sec) 1.63 % obscuration per meter	Ionization Alarm Times (sec) 0.82 % obscuration per meter
DCAS009	Real - 7	Flaming Mattress, inside foam only	Did not sustain burning	70	180	DNA (.35 at 379sec)	DNA (.35 at 379sec)	DNA (.35 at 379sec)	47	43	39
DCAS010	Real - 8	Flaming Mattress with bedsread, blanket, and 2 sheets, blankets hanging loose		60	245	380	103	103	49	45	45
DCAS011	Real - 24	Todco wallboard, 10cm wide x 30 cm high	burner 9 cm from material	62	191	273	173	114	80	72	64
DCAS012	Real - 2	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 1.5 m from ceiling		105	807	DNA (5.58 at 760sec)	365	202	223	122	118
DCAS013	Real - 8	Flaming Mattress with bedsread, blanket, and 2 sheets, blankets hanging loose		90	234	DNA (10.24 at 250sec)	137	137	70	49	49
DCAS014	Real - 23	Reiley Benton insulation, 10 cm wide x 30 cm high		65	150	DNA (9.67 at 287sec)	40	40	49	45	45
DCAS015	Real - 6	Smoldering Mattress with bedspread, blanket, and 2 sheets		60	2400	1921	1375	771	1916	1400	1350
DCAS016	Real - 6	Smoldering Mattress with bedspread, blanket, and 2 sheets		60		1580	1085	762	2151	1349	1249
DCAS017	Real - 6	Smoldering Mattress with bedspread, blanket, and 2 sheets, no finished edges		60	2400	2516	1199	595	DNA (3.94 at 2982sec)	1618	1518
DCAS018	Real - 11	Laundry Pile		60	245 (manually extinguished)	263	74	36	36	32	32
DCAS019	Real - 24	Todco wallboard, 10cm wide x 30 cm high		70	185	182	165	119	64	47	47
DCAS020	Real - 1	Meker burner on side against marinite		75	540	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec
DCAS021	Real - 1	Meker burner on side against marinite		80	540	DNA - No Change - Use 510 sec	DNA - No Change - Use 510 sec	DNA - No Change - Use 510 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec
DCAS022	Real - 1	Meker burner vertical		90	540	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec
DCAS023	Real - 1	Meker burner vertical		60	540	DNA - No Change - Use 480 sec	DNA - No Change - Use 480 sec	DNA - No Change - Use 480 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec

Table 5. Summary of Tests Conducted and Response Times of Photoelectric and Ionization Smoke Detectors

Test ID	Scenario Type and No. (Real/Nuisance)	Source Description	Comments	Ignition/Start Time (seconds)	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec)			Ionization Alarm Times (sec)		
						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter
DCAS024	Real - 2	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 1.5 m from ceiling		90	822	DNA (5.83 at 775sec)	347	200	267	204	133
DCAS025	Real - 2	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 1.5 m from ceiling		88	789	DNA (5.48 at 797sec)	332	176	214	176	172
DCAS026	Real - 2	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 1.5 m from ceiling		80	794	DNA (5.25 at 805sec)	369	222	293	210	201
DCAS027	Real - 3	JP-5, 50 mL, 7.7x7.7x2.2 cm pan		178	1101	175	66	61	87	74	74
DCAS028	Real - 3	JP-5, 25 mL, 7.7x7.7x2.2 cm pan		100	605	198	89	55	85	76	68
DCAS029	Real - 1	Bunsen Burner, 7.62 cm flame		90	748	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec
DCAS030	Real - 3	JP-5, 25 mL, 7.7x7.7x2.2 cm pan,	ODM 0-5V very noisy	90	599	174	52	48	77	65	61
DCAS031	Real - 3	JP-5, 25 mL, 7.7x7.7x2.2 cm pan,		95	570	131	56	47	102	81	68
DCAS032	Real - 3	JP-5, 25 mL, 7.7x7.7x2.2 cm pan,		95	558	190	85	60	102	81	77
DCAS033	Real - 4	JP-8, 25 mL, 7.7x7.7x2.2 cm pan,		145	648	144	69	65	69	65	60
DCAS034	Real - 4	JP-8, 25 mL, 7.7x7.7x2.2 cm pan,		105	285	134	62	54	79	67	54
DCAS035	Real - 5	Alcohol (70%), 50 mL, 7.7x7.7x2.2 cm pan		113	559	DNA (.18 at 516sec)	DNA (.18 at 516sec)	DNA (.18 at 516sec)	DNA (1.47 at 520sec)	DNA (1.47 at 520sec)	512
DCAS036	Real - 5	Alcohol (70%), 100 mL, 12.5x12.5x2.2 cm pan		95	416	DNA (.17 at 249sec)	DNA (.17 at 249sec)	DNA (.17 at 249sec)	DNA (2.68 at 287sec)	199	178
DCAS037	Real - 5	Alcohol (70%), 150 mL, 12.5x12.5x2.2 cm pan		95	564	DNA (.44 at 564sec)	DNA (.44 at 564sec)	DNA (.44 at 564sec)	DNA (4.1 at 413sec)	220	174
DCAS038	Real - 5	Alcohol (70%), 150 mL, 12.5x12.5x2.2 cm pan		80	573	DNA (.4 at 520sec)	DNA (.4 at 520sec)	DNA (.4 at 520sec)	DNA (3.93 at 470sec)	252	197
DCAS039	Real - 8	Flaming mattress, loose blankets, bunsen burner with 7.62 cm flame		60	188	DNA (0.2 at 200sec)	DNA (0.2 at 200sec)	DNA (0.2 at 200sec)	DNA (3.16 at 149 sec)	103	103
DCAS040	Real - 8	Flaming mattress, loose blankets, bunsen burner with 7.62 cm flame		60	208	DNA - Use 133 sec	DNA - Use 133 sec	DNA - Use 133 sec	87	83	78
DCAS041	Real - 2	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 1.5 m from ceiling		65	729	DNA (7.21 at 724sec)	200	120	204	120	116
DCAS042	Real - 24	Todco wallboard, 10cm wide x 30.5 cm high	burner 1.5 cm from material	105	405	DNA (3.43 at 214sec)	138	130	163	134	134

Table 5. Summary of Tests Conducted and Response Times of Photoelectric and Ionization Smoke Detectors

Test ID	Scenario Type and No. (Real/Nuisance)	Source Description	Comments	Ignition/Start Time (seconds)	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec)			Ionization Alarm Times (sec)		
						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter
DCAS043	Real - 24	Todco wallboard, 10cm wide x 30.5 cm high	burner 1.5 cm from material	85	385	208	167	158	162	146	141
DCAS044	Real - 25	Hexcel panel, 10 cm wide x 30 cm high	burner (small) 1.5 cm from material	85	441	DNA (.64 at 288sec)	DNA (.64 at 288sec)	DNA (.64 at 288sec)	233	187	183
DCAS045	Real - 25	Hexcel panel, 10 cm wide x 30 cm high	burner (small) 1.5 cm from material	85	445	DNA (2.38 at 289sec)	272	251	297	251	247
DCAS046	Real - 23	Reiley Benton insulation, 30 cm wide x 20 cm high	meker burner on side 2 cm from material, 12.7 cm flame	95	395	61	56	56	56	52	52
DCAS047	Real - 23	Reiley Benton insulation, 30 cm wide x 20 cm high	meker burner on side 2 cm from material, 12.7 cm flame	95	395	73	52	52	64	56	56
DCAS048	Real - 10	Smoldering Pillow, 15.2x15.2 cm		60	4500	3871	607	557	4299	3024	1664
DCAS049	Real - 10	Smoldering Pillow, 24.5x32 cm, with pillow case (26x34 cm)		60	4500	2579	468	452	2650	2180	1291
DCAS050	Real - 10	Smoldering Pillow, 22x34 cm, with pillow case	pillow positioned .6 m from North wall and 1.83 m from East wall	90	4800	DNA (2.97 at 4609sec)	3741	3691	DNA - Use 2789 sec	DNA - Use 2789 sec	DNA - Use 2789 sec
DCAS053	Real - 2	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 2.4 m from ceiling	pan positioned 6 ft from North wall	60	746	DNA (9.58 at 703sec)	150	78	137	103	87
DCAS054	Real - 11	Laundry Pile	pile positioned 1.83 m from North wall and 24.4 m from East wall, photoelectric	60	1836	Not operational	Not operational	Not operational	70	70	70
DCAS055	Real - 10	Smolder Pillow, 22x34 cm, with pillow case	pillow positioned 1 m from North wall, 24.4 m from East wall, and 1.5 m below ceiling	60	5745	DNA (.18 at 1945sec)	DNA (.18 at 1945sec)	DNA (.18 at 1945sec)	DNA - No Change - Use 2700 sec	DNA - No Change - Use 2700 sec	DNA - No Change - Use 2700 sec
DCAS057	Real - 11	Laundry Pile	pile positioned 1 m from North wall, 24.4 m from East wall, and 2.4 m below ceiling, photoelectric malfunction	60	1965 (manually extinguished)	Not operational	Not operational	Not operational	162	116	99
DCAS058	Real - 18	Office Trash Can	ignited with match, rapid fire growth, SO2 sensor not working	60	300-360	DNA (3.58 at 477sec)	108	83	45	41	41
DCAS059	Real - 18	Office Trash Can	attempted ignition with cigarette then ignited with heating coil, SO2 sensor not working	60 (cig) - 810 (heating coil on) 1255 (flaming)	645 (cigarette out) - 1550 (flames out)	DNA (13.01 at 1220sec)	1178	1170	1224	1220	1220
DCAS060	Real - 18	Office Trash Can	SO2 sensor not working	60 (heating coil on) - 576 (flaming)	600-750	389	250	238	435	355	342

Table 5. Summary of Tests Conducted and Response Times of Photoelectric and Ionization Smoke Detectors

Test ID	Scenario Type and No. (Real/Nuisance)	Source Description	Comments	Ignition/Start Time (seconds)	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec) 11 % obscuration per meter	Photoelectric 1.63 % obscuration per meter	Photoelectric 0.82 % obscuration per meter	Ionization Alarm Times (sec) 4.2 % obscuration per meter	Ionization 1.63 % obscuration per meter	Ionization 0.82 % obscuration per meter
DCAS061	Real - 18	Office Trash Can	repeat of dcas060, SO2 sensor not working	60 (heating coil on) - 1327	1455	1199	1169	960	1295	1216	1203
DCAS062	Real - 18	Office Trash Can	SO2 sensor not working	60 (heating coil on) - 604 (flaming)	779	DNA (10.43 at 758sec)	427	414	574	570	570
DCAS063	Real - 1	Meker burner, horizontal with 12.7 cm flame	SO2 sensor not working	60	660	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA (-1.57 at 548sec)	DNA (-1.57 at 548sec)	DNA (-1.57 at 548sec)
DCAS064	Real - 23	Reliey Benton insulation, 20 cm wide x 30 cm high	SO2 sensor not working	60	380	53	45	45	49	49	49
DCAS065	Real - 25	Hexcel panel, 10 cm wide x 30 cm high	SO2 sensor not working	71	720	DNA - No Change - Use 660 sec	DNA - No Change - Use 660 sec	DNA - No Change - Use 660 sec	DNA (1.7 at 64sec)	DNA (1.7 at 64sec)	55
DCAS066	Real - 9	Flaming mattress with tucked blankets	SO2 sensor not working	60	710	DNA (4.06 at 889sec)	414	364	142	66	62
DCAS067	Real - 9	Flaming mattress with tucked blankets	mattress positioned 1.5 m below ceiling, SO2 sensor not working	60	687	293	188	171	125	58	53
DCAS068	Real - 9	Flaming mattress with tucked blankets	Repeat of dcas067 with smaller flame from burner, mattress positioned 1.5 m below ceiling, SO2 sensor not working	60	660	DNA (.56 at 590sec)	DNA (.56 at 590sec)	DNA (.56 at 590sec)	565	200	192
DCAS073	Nuisance - 2	Normal Toasting, 8 slices at once, 8 total		60	325	DNA - No Change - Use 265 sec	DNA - No Change - Use 265 sec	DNA - No Change - Use 265 sec	DNA - Use 284 sec	DNA - Use 284 sec	DNA - Use 284 sec
DCAS074	Nuisance - 5	Grinding steel	Steel setup 2.4 m below ceiling	60	841	DNA (.89 at 725sec)	DNA (.89 at 725sec)	DNA (.89 at 725sec)	666	288	91
DCAS075	Nuisance - 1	Burning Toast, one slice		60	480	649	595	574	515	498	490
DCAS076	Nuisance - 1	Burning Toast, one slice		60	480	422	380	376	519	431	368
DCAS077	Nuisance - 1	Burning Toast, one slice		60	480	372	355	347	385	355	343
DCAS080	Nuisance - 2	Normal Toasting, 8 slices at a time, 24 total		60	610	DNA - No Change - Use 550 sec	DNA - No Change - Use 550 sec	DNA - No Change - Use 550 sec	548	364	351
DCAS081	Nuisance - 2	Normal Toasting, 8 slices at a time, 24 total		60	578	DNA - No Change - Use 518 sec	DNA - No Change - Use 518 sec	DNA - No Change - Use 518 sec	540	376	363

Table 5. Summary of Tests Conducted and Response Times of Photoelectric and Ionization Smoke Detectors

Test ID	Scenario Type and No. (Real/Nuisance)	Source Description	Comments	Ignition/Start Time (seconds)	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec)			Ionization Alarm Times (sec)		
						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter
DCAS082	Nuisance - 5	Grinding steel	repeat of dcas074	60	620	DNA (.38 at 859sec)	DNA (.38 at 859sec)	DNA (.38 at 859sec)	DNA - Use 616 sec	DNA - Use 616 sec	DNA - Use 616 sec
DCAS083	Nuisance - 6	Grinding cinder block, 2.4 m below ceiling		60	939	918	318	314	DNA - No Change - Use 879 sec	DNA - No Change - Use 879 sec	DNA - No Change - Use 879 sec
DCAS084	Nuisance - 6	Grinding cinder block, 2.4 m below ceiling	repeat of dcas083	60	750	926	922	536	DNA - No Change - Use 690 sec	DNA - No Change - Use 690 sec	DNA - No Change - Use 690 sec
DCAS085	Nuisance - 4	Cutting steel with acetylene torch, 2.4 m below ceiling		75	397	DNA (.31 at 305sec)	DNA (.31 at 305sec)	DNA (.31 at 305sec)	16	8	8
DCAS087	Nuisance - 4	Cutting steel with acetylene torch, 2.4 m below ceiling	repeat of dcas085	150	465	DNA - No Change - Use 315 sec	DNA - No Change - Use 315 sec	DNA - No Change - Use 315 sec	129	66	62
DCAS088	Nuisance - 4	Cutting steel with acetylene torch, 2.4 m below ceiling	repeat of dcas085	85	430	DNA (4.13 at 386sec)	361	353	227	9	9
DCAS089	Nuisance - 3	Welding steel, 2.4 m below ceiling		66	540	DNA (3.86 at 522sec)	161	119	DNA (3.47 at 526sec)	291	169
DCAS090	Nuisance - 3	Welding steel, 2.4 m below ceiling	repeat of dcas089	80	900	DNA (6.08 at 738sec)	185	130	617	277	252
DCAS091	Nuisance - 3	Welding steel, 2.4 m below ceiling	repeat of dcas089	156	756	DNA (5.58 at 549sec)	138	117	465	151	130
DCAS092	Nuisance - 7	Cutting lauan with circular saw		60	660	DNA (0.63 at 352sec)	DNA (0.63 at 352sec)	DNA (0.63 at 352sec)	DNA - Use 360 sec	DNA - Use 360 sec	DNA - Use 360 sec
DCAS093	Nuisance - 7	Cutting lauan with circular saw	repeat of dcas092, circuit breaker tripped unable to complete test	125	525	DNA (.63 at 391sec)	DNA (.63 at 391sec)	DNA (.63 at 391sec)	DNA - Use 97 sec	DNA - Use 97 sec	DNA - Use 97 sec
DCAS094	Nuisance - 7	Cutting lauan with circular saw	repeat of dcas092, mic pump not turned on	60	690	DNA (.56 at 66sec)	DNA (.56 at 66sec)	DNA (.56 at 66sec)	DNA - Use 322 sec	DNA - Use 322 sec	DNA - Use 322 sec
DCAS095	Nuisance - 7	Cutting lauan with circular saw	repeat of dcas092	60	495	DNA (.46 at 800sec)	DNA (.46 at 800sec)	DNA (.46 at 800sec)	DNA (-1.04 at 443sec)	DNA (-1.04 at 443sec)	DNA (-1.04 at 443sec)
DCAS096	Nuisance - 8	Burning popcorn in microwave		60	780	440	381	377	DNA - Use 461 sec	DNA - Use 461 sec	DNA - Use 461 sec
DCAS097	Nuisance - 8	Burning popcorn in microwave	repeat of dcas096	60	780	DNA (10.17 at 452sec)	389	376	DNA - Use 708 sec	DNA - Use 708 sec	DNA - Use 708 sec
DCAS098	Nuisance - 8	Burning popcorn in microwave	repeat of dcas096	60	780	422	401	397	DNA - Use 683 sec	DNA - Use 683 sec	DNA - Use 683 sec

Table 5. Summary of Tests Conducted and Response Times of Photoelectric and Ionization Smoke Detectors

Test ID	Scenario Type and No. (Real/Nuisance)	Source Description	Comments	Ignition/Start Time (seconds)	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec) 11 % obscuration per meter	Photoelectric Alarm Times (sec) 1.63 % obscuration per meter	Photoelectric Alarm Times (sec) 0.82 % obscuration per meter	Ionization Alarm Times (sec) 4.2 % obscuration per meter	Ionization Alarm Times (sec) 1.63 % obscuration per meter	Ionization Alarm Times (sec) 0.82 % obscuration per meter
DCAS099	Real - 12	Smoldering LSDSGU-14		65	1083	930	930	930	934	930	930
DCAS100	Real - 13	Smoldering LSTHOF-9		60	900	989	964	960	1048	1006	1002
DCAS101	Real - 13	Smoldering LSTHOF-9	repeat of dcas100	60	1073	893	821	775	DNA (3.21 at 1023sec)	947	939
DCAS102	Real - 13	Smoldering LSTHOF-9	repeat of dcas100	60	1020	603	586	569	DNA (3.27 at 725sec)	662	645
DCAS103	Real - 12	Smoldering LSDSGU-14	repeat of dcas099	60	1170	766	678	653	DNA - Use 1010 sec	DNA - Use 1010 sec	DNA - Use 1010 sec
DCAS104	Real - 12	Smoldering LSDSGU-14	repeat of dcas099	60	1200	1056	855	813	DNA (1.9 at 1221sec)	1212	1136
DCAS105	Real - 14	Smoldering LSTPNW-1-1/2		67	549	382	290	277	DNA (.63 at 449sec)	DNA (.63 at 449sec)	DNA (.63 at 449sec)
DCAS106	Real - 14	Smoldering LSTPNW-1-1/2	repeat of dcas106	103	1206	DNA (10.97 at 782sec)	589	564	DNA - Use 1103 sec	DNA - Use 1103 sec	DNA - Use 1103 sec
DCAS107	Real - 14	Smoldering LSTPNW-1-1/2	repeat of dcas106	103	1200	983	669	610	DNA - Use 1043 sec	DNA - Use 1043 sec	DNA - Use 1043 sec
DCAS109	Real - 17	Igniting LSDSGU-50	cables ignited with torch after being heated with welder	60	733	DNA (2.48 at 628sec)	616	607	DNA (1.62 at 733sec)	DNA (1.62 at 733sec)	595
DCAS110	Real - 15	Igniting LSDGU-14	cables ignited with torch after being heated with welder	60	544	477	414	405	477	464	460
DCAS111	Real - 15	Igniting LSDGU-14	repeat of dcas110, cables ignited with torch after being heated with welder	60	764	611	552	535	519	498	473
DCAS112	Real - 15	Igniting LSDGU-14	repeat of dcas110, cables ignited with torch after being heated with welder	60	752	632	519	498	527	489	477
DCAS113	Real - 16	Igniting LSTHOF-9	cables ignited with torch after being heated with welder	60	1122	DNA (5.64 at 1002sec)	674	624	720	653	595
DCAS114	Real - 16	Igniting LSTHOF-9	repeat of dcas113, cables ignited with torch after being heated with welder	60	870	DNA (8.44 at 872sec)	729	570	738	603	561

Table 5. Summary of Tests Conducted and Response Times of Photoelectric and Ionization Smoke Detectors

Test ID	Scenario Type and No. (Real/Nuisance)	Source Description	Comments	Ignition/Start Time (seconds)	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec)			Ionization Alarm Times (sec)		
						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per motor
DCAS115	Real - 16	Igniting LSTHOF-9	repeat of dcas113, cables ignited with torch after being heated with welder	73	673	DNA (9.11 at 506sec)	418	401	535	434	426
DCAS116	Real - 1	Meker burner, horizontal, 3.2 cm flame	MIC malfunction	68		DNA - No Change - Use 180 sec	DNA - No Change - Use 180 sec	DNA - No Change - Use 180 sec	DNA - No Change - Use 180 sec	DNA - No Change - Use 180 sec	DNA - No Change - Use 180 sec
DCAS117	Real - 19	NH elastomeric foam with rewettable glass lagging, painted	MIC malfunction	76	893	DNA (.72 at 201sec)	DNA (.72 at 201sec)	DNA (.72 at 201sec)	192	184	180
DCAS118	Real - 19	NH elastomeric foam with rewettable glass lagging, painted	repeat of dcas117	68	878	DNA (.26 at 800sec)	DNA (.26 at 800sec)	DNA (.26 at 800sec)	267	242	229
DCAS119	Real - 19	NH elastomeric foam with rewettable glass lagging, painted	repeat of dcas117	71	911	DNA (1.09 at 345sec)	DNA (1.09 at 345sec)	257	248	148	97
DCAS120	Real - 19	NH elastomeric foam with rewettable glass lagging, painted	repeat of dcas117 with a cut in lagging and insulation	70	611	DNA (.14 at 190sec)	DNA (.14 at 190sec)	DNA (.14 at 190sec)	287	195	186
DCAS121	Real - 20	NH elastomeric foam with rewettable glass lagging, painted, soaked with oil	MIC malfunction	81	600	DNA (6.91 at 297sec)	188	184	186	179	108
DCAS122	Real - 20	NH elastomeric foam with rewettable glass lagging, painted, soaked with oil	repeat of dcas121	69	660	DNA (5.37 at 359sec)	199	162	157	74	69
DCAS123	Real - 20	NH elastomeric foam with rewettable glass lagging, painted, soaked with oil	repeat of dcas121	73	684	DNA (2.61 at 296sec)	275	242	326	242	229
DCAS124	Real - 22	Calcium silicate insulation with glass cloth lagging, painted, soaked with oil		68	675	DNA (2.35 at 121sec)	96	84	138	88	79
DCAS125	Real - 22	Calcium silicate insulation with glass cloth lagging, painted, soaked with oil	repeat of dcas124	66	678	DNA (2.8 at 215sec)	158	144	240	215	211
DCAS126	Real - 22	Calcium silicate insulation with glass cloth lagging, painted, soaked with oil	repeat of dcas124	81	845	DNA (4. at 544sec)	133	57	141	57	53
DCAS127	Real - 21	Calcium silicate insulation with glass cloth lagging, painted		68	731	DNA (.48 at 218sec)	DNA (.48 at 218sec)	DNA (.48 at 218sec)	DNA (3.92 at 239sec)	193	184
DCAS128	Real - 21	Calcium silicate insulation with glass cloth lagging, painted	repeat of dcas127	65	695	DNA (2.04 at 279sec)	266	241	250	199	182
DCAS129	Real - 21	Calcium silicate insulation with glass cloth lagging, painted	repeat of dcas127	62	674	DNA (1.25 at 236sec)	DNA (1.25 at 236sec)	161	DNA (3.56 at 446sec)	169	157

Table 5. Summary of Tests Conducted and Response Times of Photoelectric and Ionization Smoke Detectors

Test ID	Scenario Type and No. (Real/Nuisance)	Source Description	Comments	Ignition/Start Time (seconds)	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec)			Ionization Alarm Times (sec)		
						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter
DCAS130	Nuisance - 12	Smoking Cigarettes, 8 total		65	745	DNA (3.47 at 648sec)	585	292	DNA - Use 632 sec	DNA - Use 632 sec	DNA - Use 632 sec
DCAS131	Nuisance - 12	Smoking Cigarettes, 7 total		63	533	DNA (2.48 at 428sec)	122	105	DNA (.02 at 399sec)	DNA (.02 at 399sec)	DNA (.02 at 399sec)
DCAS132	Nuisance - 12	Smoking Cigarettes, 12 total		65	623	DNA (3.34 at 569sec)	305	116	DNA (.84 at 498sec)	DNA (.84 at 498sec)	485
DCAS133	Nuisance - 10	Electric heater, 1.5 m below ceiling		60	950	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec
DCAS134	Nuisance - 10	2 Electric heaters and 1 halogen worklight	units positioned 3.1 m from North wall and 1.5 m below ceiling	60	660	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 150 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 150 sec
DCAS135	Nuisance - 10	2 Electric heaters and 1 halogen worklight	repeat of dcas134	60	660	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 240 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 240 sec
DCAS136	Nuisance - 10	2 Electric heaters and 1 halogen worklight	repeat of dcas134	60	660	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 180 sec)	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 180 sec)
DCAS137	Nuisance - 11	People Talking, 5 people total		60	1260	DNA - No Change - Use 1200 sec)	DNA - No Change - Use 1200 sec)	DNA - No Change - Use 1200 sec)	DNA - No Change - Use 1200 sec)	DNA - No Change - Use 1200 sec)	DNA - No Change - Use 1200 sec)
DCAS138	Nuisance - 11	People Talking, 4 people total	repeat of dcas 137	60	2010	DNA - No Change - Use 1950 sec	DNA - No Change - Use 1950 sec	DNA - No Change - Use 1950 sec	DNA - No Change - Use 1950 sec	DNA - No Change - Use 1950 sec	DNA - No Change - Use 1950 sec
DCAS139	Nuisance - 9	Gas Engine		60	960	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA (.5 at 884sec)	DNA (.5 at 884sec)	DNA (.5 at 884sec)
DCAS140	Nuisance - 9	Gas Engine	repeat of dcas139	60	960	DNA - No Change - Use 900 sec	DNA - No Change - Use 660 sec	DNA - No Change - Use 360 sec	DNA - (1.13 at 70sec)	DNA - (1.13 at 70sec)	DNA - (1.13 at 70sec)

Table 5. Summary of Tests Conducted and Response Times of Photoelectric and Ionization Smoke Detectors

Test ID	Scenario Type and No. (Real/Nuisance)	Source Description	Comments	Ignition/Start Time (seconds)	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec)			Ionization Alarm Times (sec)		
						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter
DCAS141	Nuisance - 9	Gas Engine	repeat of dcas139	60	960	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 540 sec	DNA - (.69 at 49sec)	DNA - (.69 at 49sec)	DNA - (.69 at 49sec)
DCAS142	Nuisance - 12	Smoking Cigarettes, 4 people, 12 cigarettes		60	890	DNA (8.29 at 792sec)	171	171	DNA (2.08 at 733sec)	670	381
DCAS143	Nuisance - 12	Smoking Cigarettes, 4 people, 14 cigarettes	repeat of dcas142	60	999	DNA (7.36 at 456sec)	154	99	DNA (2.45 at 892sec)	875	380
DCAS144	Nuisance - 12	Smoking Cigarettes, 4 people, 17 cigarettes	repeat of dcas142	60	976	DNA (5.03 at 769sec)	241	161	DNA (2.88 at 719sec)	312	308
DCAS145	Real - 2	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 2.4 m from ceiling		60	767	DNA (8.85 at 728sec)	116	66	120	61	57

Table 6. Summary of Tests conducted, organized by scenario

Source Type/ Scenario No./ Description	Test ID	Source Description	Comments	Ignition/ Start Tim (seconds	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec)			Ionization Alarm Times (sec)		
						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter
Real - 1 Propane Burners	DCAS020	Meker burner on side against marinite		75	540	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec
	DCAS021	Meker burner on side against marinite		80	540	DNA - No Change - Use 510 sec	DNA - No Change - Use 510 sec	DNA - No Change - Use 510 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec
	DCAS022	Meker burner vertical		90	540	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec
	DCAS023	Meker burner vertical		60	540	DNA - No Change - Use 480 sec	DNA - No Change - Use 480 sec	DNA - No Change - Use 480 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec
	DCAS029	Bunsen Burner, 7.62 cm flame		90	748	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 450 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec	DNA - No Change - Use 390 sec
	DCAS063	Meker burner, horizontal with 12.7 cm flame	SO2 sensor not working	60	680	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA (-1.57 at 548sec)	DNA (-1.57 at 548sec)	DNA (-1.57 at 548sec)
	DCAS116	Meker burner, horizontal, 3.2 cm flame	MIC malfunction	68		DNA - No Change - Use 180 sec	DNA - No Change - Use 180 sec	DNA - No Change - Use 180 sec	DNA - No Change - Use 180 sec	DNA - No Change - Use 180 sec	DNA - No Change - Use 180 sec
Real - 2 Heptane pool fire	DCAS012	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 1.5 m from ceiling		105	807	DNA (5.58 at 760sec)	365	202	223	122	118
	DCAS024	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 1.5 m from ceiling		90	822	DNA (5.83 at 775sec)	347	200	267	204	133
	DCAS025	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 1.5 m from ceiling		88	789	DNA (5.48 at 797sec)	332	176	214	176	172
	DCAS026	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 1.5 m from ceiling		80	794	DNA (5.25 at 805sec)	369	222	293	210	201
	DCAS041	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 1.5 m from ceiling		65	729	DNA (7.21 at 724sec)	200	120	204	120	116
	DCAS053	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 2.4 m from ceiling	pan positioned 1.8 ft from North wall	60	746	DNA (9.58 at 703sec)	150	78	137	103	87
	DCAS145	Heptane, 100 mL, 7.7x7.7x2.2 cm pan, 2.4 m from ceiling		60	767	DNA (8.85 at 728sec)	116	66	120	61	57
Real - 3 JP-5 pool fire	DCAS027	JP-5, 50 mL, 7.7x7.7x2.2 cm pan		178	1101	175	66	81	87	74	74
	DCAS028	JP-5, 25 mL, 7.7x7.7x2.2 cm pan		100	605	198	89	55	85	76	68
	DCAS030	JP-5, 25 mL, 7.7x7.7x2.2 cm pan,	ODM 0-5V very noisy	90	599	174	52	48	77	65	61
	DCAS031	JP-5, 25 mL, 7.7x7.7x2.2 cm pan,		95	570	131	56	47	102	81	68
	DCAS032	JP-5, 25 mL, 7.7x7.7x2.2 cm pan,		85	558	190	85	60	102	81	77
Real - 4 JP-8 pool fire	DCAS033	JP-8, 25 mL, 7.7x7.7x2.2 cm pan,		145	648	144	69	65	69	65	60
	DCAS034	JP-8, 25 mL, 7.7x7.7x2.2 cm pan,		105	285	134	62	54	79	67	54
Real - 5 Alcohol pool fire	DCAS035	Alcohol (70%), 50 mL, 7.7x7.7x2.2 cm pan		113	559	DNA (.18 at 516sec)	DNA (.18 at 516sec)	DNA (.18 at 516sec)	DNA (1.47 at 520sec)	DNA (1.47 at 520sec)	512
	DCAS036	Alcohol (70%), 100 mL, 12.5x12.5x2.2 cm pan		95	416	DNA (.17 at 249sec)	DNA (.17 at 249sec)	DNA (.17 at 249sec)	DNA (2.68 at 287sec)	199	178
	DCAS037	Alcohol (70%), 150 mL, 12.5x12.5x2.2 cm pan		95	564	DNA (.44 at 564sec)	DNA (.44 at 564sec)	DNA (.44 at 564sec)	DNA (4.1 at 413sec)	220	174
	DCAS038	Alcohol (70%), 150 mL, 12.5x12.5x2.2 cm pan		80	573	DNA (.4 at 520sec)	DNA (.4 at 520sec)	DNA (.4 at 520sec)	DNA (3.93 at 470sec)	252	197

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						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter
Real - 6 Smolderin Mattress	DCAS015	Smoldering Mattress with bedspread, blanket, and 2 sheets		60	2400	1921	1375	771	1916	1400	1350
	DCAS016	Smoldering Mattress with bedspread, blanket, and 2 sheets		60		1580	1085	762	2151	1349	1249
	DCAS017	Smoldering Mattress with bedspread, blanket, and 2 sheets, no finished edges		60	2400	2516	1199	595	DNA (3.94 at 2982sec)	1618	1518
Real - 7 Flaming Mattress (Foam Only)	DCAS009	Flaming Mattress, inside foam only	Did not sustain burning	70	180	DNA (.35 at 379sec)	DNA (.35 at 379sec)	DNA (.35 at 379sec)	47	43	39
Real - 8 Flaming Mattress (Loose Bedding)	DCAS010	Flaming Mattress with bedsread, blanket, and 2 sheets, blankets hanging loose		60	245	380	103	103	49	45	45
	DCAS013	Flaming Mattress with bedsread, blanket, and 2 sheets, blankets hanging loose		90	234	DNA (10.24 at 250sec)	137	137	70	49	49
	DCAS039	Flaming mattress, loose blankets, bunsen burner with 7.62 cm flame		60	188	DNA (0.2 at 200sec)	DNA (0.2 at 200sec)	DNA (0.2 at 200sec)	DNA (3.16 at 149 sec)	103	103
	DCAS040	Flaming mattress, loose blankets, bunsen burner with 7.62 cm flame		60	208	DNA - Use 133 sec	DNA - Use 133 sec	DNA - Use 133 sec	87	83	78
Real - 9 Flaming Mattress (Tucked Bedding)	DCAS066	Flaming mattress with tucked blankets	SO2 sensor not working	60	710	DNA (4.06 at 889sec)	414	384	142	66	62
	DCAS067	Flaming mattress with tucked blankets	mattress positioned 1.5 m below ceiling, SO2 sensor not working	60	687	293	188	171	125	58	53
	DCAS068	Flaming mattress with tucked blankets	Repeat of dcas067 with smaller flame from burner, mattress positioned 1.5 m below ceiling, SO2 sensor not working	60	660	DNA (.56 at 590sec)	DNA (.56 at 590sec)	DNA (.56 at 590sec)	565	200	192

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						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter
Real - 10 Smoldering Pillow	DCAS048	Smoldering Pillow, 15.2x15.2 cm		60	4500	3871	607	557	4299	3024	1664
	DCAS049	Smoldering Pillow, 24.5x32 cm, with pillow case (26x34 cm)		60	4500	2579	468	452	2650	2180	1291
	DCAS050	Smoldering Pillow, 22x34 cm, with pillow case	pillow positioned .6 m from North wall and 1.83 m from East wall	90	4600	DNA (2.97 at 4609sec)	3741	3691	DNA - Use 2789 sec	DNA - Use 2789 sec	DNA - Use 2789 sec
	DCAS055	Smolder Pillow, 22x34 cm, with pillow case	pillow positioned 1 m from North wall, 24.4 m from East wall, and 1.5 m below ceiling	60	5745	DNA (.18 at 1945sec)	DNA (.18 at 1945sec)	DNA (.18 at 1945sec)	DNA - No Change - Use 2700 sec	DNA - No Change - Use 2700 sec	DNA - No Change - Use 2700 sec
Real - 11 Laundry Pile fire	DCAS018	Laundry Pile		60	245 (manually extinguished)	263	74	36	36	32	32
	DCAS054	Laundry Pile	pile positioned 1.83 m from North wall and 24.4 m from East wall, photoelectric malfunction	60	1836	Not operational	Not operational	Not operational	70	70	70
Real - 11 cont.	DCAS057	Laundry Pile	pile positioned 1 m from North wall, 24.4 m from East wall, and 2.4 m below ceiling, photoelectric malfunction	60	1965 (manually extinguished)	Not operational	Not operational	Not operational	162	116	99
Real - 12 Smoldering Electrical Cable LSDSGU-14	DCAS099	Smoldering LSDSGU-14		65	1083	930	930	930	934	930	930
	DCAS103	Smoldering LSDSGU-14	repeat of dcas099	60	1170	766	678	653	DNA - Use 1010 sec	DNA - Use 1010 sec	DNA - Use 1010 sec
	DCAS104	Smoldering LSDSGU-14	repeat of dcas099	60	1200	1056	855	813	DNA (1.9 at 1221sec)	1212	1136
Real - 13 Smoldering Electrical Cable LSTHOF-9	DCAS100	Smoldering LSTHOF-9		60	900	989	964	960	1048	1006	1002
	DCAS101	Smoldering LSTHOF-9	repeat of dcas100	60	1073	893	821	775	DNA (3.21 at 1023sec)	947	939
	DCAS102	Smoldering LSTHOF-9	repeat of dcas100	60	1020	603	586	569	DNA (3.27 at 725sec)	662	645

Table 6. Summary of Tests conducted, organized by scenario

Source Type/ Scenario No./ Description	Test ID	Source Description	Comments	Ignition/ Start Tim (seconds	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec)			Ionization Alarm Times (sec)		
						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter
Real - 14 Smoldering Electrical Cable LSTPNW-1-1/2	DCAS105	Smoldering LSTPNW-1-1/2		67	549	382	290	277	DNA (.63 at 449sec)	DNA (.63 at 449sec)	DNA (.63 at 449sec)
	DCAS106	Smoldering LSTPNW-1-1/2	repeat of dcas106	103	1206	DNA (10.97 at 782sec)	589	564	DNA - Use 1103 sec	DNA - Use 1103 sec	DNA - Use 1103 sec
	DCAS107	Smoldering LSTPNW-1-1/2	repeat of dcas106	103	1200	963	669	610	DNA - Use 1043 sec	DNA - Use 1043 sec	DNA - Use 1043 sec
Real - 15 Flaming Electrical Cable LSDGU-14	DCAS110	Igniting LSDGU-14	cables ignited with torch after being heated with welder	60	544	477	414	405	477	464	460
	DCAS111	Igniting LSDGU-14	repeat of dcas110, cables ignited with torch after being heated with welder	60	764	611	552	535	519	498	473
	DCAS112	Igniting LSDGU-14	repeat of dcas110, cables ignited with torch after being heated with welder	60	752	632	519	498	527	489	477
Real - 16 Flaming Electrical Cable LSTHOF-9	DCAS113	Igniting LSTHOF-9	cables ignited with torch after being heated with welder	60	1122	DNA (5.64 at 1002sec)	674	624	720	653	595
	DCAS114	Igniting LSTHOF-9	repeat of dcas113, cables ignited with torch after being heated with welder	60	870	DNA (8.44 at 872sec)	729	570	738	603	561
	DCAS115	Igniting LSTHOF-9	repeat of dcas113, cables ignited with torch after being heated with welder	73	673	DNA (9.11 at 506sec)	418	401	535	434	426
Real - 17 Flaming Electrical Cable LSDSGU-50	DCAS109	Igniting LSDSGU-50	cables ignited with torch after being heated with welder	60	733	DNA (2.48 at 628sec)	616	607	DNA (1.62 at 733sec)	DNA (1.62 at 733sec)	595

Table 6. Summary of Tests conducted, organized by scenario

Source Type/ Scenario No./ Description	Test ID	Source Description	Comments	Ignition/ Start Tim (seconds	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec)			Ionization Alarm Times (sec)		
						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter
Real - 18 Office Trash Can Fire	DCAS058	Office Trash Can	Ignited with match, rapid fire growth, SO2 sensor not working	60	300-360	DNA (3.58 at 477sec)	108	83	45	41	41
	DCAS059	Office Trash Can	attempted ignition with cigarette then ignited with glocoil, SO2 sensor not working	1:00 (cig) - 810 (glocoil on) - 1255 (flaming)	645 (cigarette out) - 1550 (flames out)	DNA (13.01 at 1220sec)	1178	1170	1224	1220	1220
	DCAS060	Office Trash Can	SO2 sensor not working	60 (glocoil on) - 576 (flaming)	600-750	389	250	238	435	355	342
	DCAS061	Office Trash Can	repeat of dcas060, SO2 sensor not working	60 (glocoil on) - 1327 (flaming)	1455	1199	1169	960	1295	1216	1203
	DCAS062	Office Trash Can	SO2 sensor not working	60 (glocoil on) - 604 (flaming)	779	DNA (10.43 at 758sec)	427	414	574	570	570
Real - 19 Pipe Insulation (NH Armaflex) Fire	DCAS117	NH elastomeric foam with rewettable glass lagging, painted	MIC malfunction	76	893	DNA (.72 at 201sec)	DNA (.72 at 201sec)	DNA (.72 at 201sec)	192	184	180
Real - 19 cont.	DCAS118	NH elastomeric foam with rewettable glass lagging, painted	repeat of dcas117	68	878	DNA (.26 at 800sec)	DNA (.26 at 800sec)	DNA (.26 at 800sec)	267	242	229
	DCAS119	NH elastomeric foam with rewettable glass lagging, painted	repeat of dcas117	71	911	DNA (1.09 at 345sec)	DNA (1.09 at 345sec)	257	248	148	97
	DCAS120	NH elastomeric foam with rewettable glass lagging, painted	repeat of dcas117 with a cut in lagging and insulation	70	611	DNA (.14 at 190sec)	DNA (.14 at 190sec)	DNA (.14 at 190sec)	287	195	186
Real - 20 Pipe Insulation coated with oil fire (NH Armaflex)	DCAS121	NH elastomeric foam with rewettable glass lagging, painted, soaked with oil	MIC malfunction	81	600	DNA (6.91 at 297sec)	188	184	196	179	108
	DCAS122	NH elastomeric foam with rewettable glass lagging, painted, soaked with oil	repeat of dcas121	69	660	DNA (5.37 at 359sec)	199	162	157	74	69
	DCAS123	NH elastomeric foam with rewettable glass lagging, painted, soaked with oil	repeat of dcas121	73	664	DNA (2.61 at 296sec)	275	242	326	242	229

Table 6. Summary of Tests conducted, organized by scenario

Source Type/ Scenario No./ Description	Test ID	Source Description	Comments	Ignition/ Start Tim (seconds	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec) 11 % obscuration per meter	Photoelectric 1.63 % obscuration per meter	Photoelectric 0.82 % obscuration per meter	Ionization Alarm Times (sec) 4.2 % obscuration per meter	Ionization 1.63 % obscuration per meter	Ionization 0.82 % obscuration per meter
Real - 21 Pipe Insulation (Calciu silicate) fire	DCAS127	Calcium silicate insulation with glass cloth lagging, painted		68	731	DNA (.48 at 218sec)	DNA (.48 at 218sec)	DNA (.48 at 218sec)	DNA (3.92 at 239sec)	193	184
	DCAS128	Calcium silicate insulation with glass cloth lagging, painted	repeat of dcas127	65	695	DNA (2.04 at 279sec)	266	241	250	199	182
	DCAS129	Calcium silicate insulation with glass cloth lagging, painted	repeat of dcas127	62	674	DNA (1.25 at 236sec)	DNA (1.25 at 236sec)	161	DNA (3.56 at 446sec)	169	157
Real - 22 Pipe Insulation coated with oil fire (Calcium silicate)	DCAS124	Calcium silicate insulation with glass cloth lagging, painted, soaked with oil		68	675	DNA (2.35 at 121sec)	96	84	138	88	79
	DCAS125	Calcium silicate insulation with glass cloth lagging, painted, soaked with oil	repeat of dcas124	66	678	DNA (2.8 at 215sec)	156	144	240	215	211
	DCAS126	Calcium silicate insulation with glass cloth lagging, painted, soaked with oil	repeat of dcas124	81	845	DNA (4. at 544sec)	133	57	141	57	53
Real - 23 Polyimi acoustic insulation	DCAS014	Relley Benton insulation, 10 cm wide x 30 cm high		65	150	DNA (9.67 at 267sec)	40	40	49	45	45
	DCAS046	Relley Benton insulation, 30 cm wide x 20 cm high	meker burner on side 2 cm from material, 12.7 cm flame	95	395	61	56	56	56	52	52
	DCAS047	Relley Benton insulation, 30 cm wide x 20 cm high	meker burner on side 2 cm from material, 12.7 cm flame	95	395	73	52	52	64	56	56
	DCAS064	Relley Benton insulation, 20 cm wide x 30 cm high	SO2 sensor not working	60	360	53	45	45	49	49	49
Real - 24 Nomex honeycomb wall panel (TODCO)	DCAS011	Todco wallboard, 10cm wide x 30 cm high	burner 9 cm from material	62	191	273	173	114	80	72	64
	DCAS019	Todco wallboard, 10cm wide x 30 cm high		70	185	182	165	119	64	47	47
	DCAS042	Todco wallboard, 10cm wide x 30.5 cm high	burner 1.5 cm from material	105	405	DNA (3.43 at 214sec)	138	130	163	134	134
	DCAS043	Todco wallboard, 10cm wide x 30.5 cm high	burner 1.5 cm from material	85	385	208	167	158	162	146	141

Table 6. Summary of Tests conducted, organized by scenario

Source Type/ Scenario No./ Description	Test ID	Source Description	Comments	Ignition/ Start Tim (seconds	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec) 11 % obscuration per meter	Photoelectric 1.63 % obscuration per meter	Photoelectric 0.82 % obscuration per meter	Ionization Alarm Times (sec) 4.2 % obscuration per meter	Ionization 1.63 % obscuration per meter	Ionization 0.82 % obscuration per meter
Real - 25 Nomex honeycomb wall panel (Hexcel)	DCAS044	Hexcel panel, 10 cm wide x 30 cm high	burner (small) 1.5 cm from material	85	441	DNA (.64 at 288sec)	DNA (.64 at 288sec)	DNA (.64 at 288sec)	233	187	183
	DCAS045	Hexcel panel, 10 cm wide x 30 cm high	burner (small) 1.5 cm from material	85	445	DNA (2.38 at 289sec)	272	251	297	251	247
	DCAS065	Hexcel panel, 10 cm wide x 30 cm high	SO2 sensor not working	71	720	DNA - No Change - Use 660 sec	DNA - No Change - Use 660 sec	DNA - No Change - Use 660 sec	DNA (1.7 at 64sec)	DNA (1.7 at 64sec)	55
Nuisance - 1 Burning Toast	DCAS075	Burning Toast, one slice		60	480	649	595	574	515	498	490
	DCAS076	Burning Toast, one slice		60	480	422	380	376	519	431	368
	DCAS077	Burning Toast, one slice		60	480	372	355	347	385	355	343
Nuisance - 2 Normal Toasting	DCAS073	Normal Toasting, 8 slices at once, 8 total		60	325	DNA - No Change - Use 265 sec	DNA - No Change - Use 265 sec	DNA - No Change - Use 265 sec	DNA - Use 284 sec	DNA - Use 284 sec	DNA - Use 284 sec
	DCAS080	Normal Toasting, 8 slices at a time, 24 total		60	610	DNA - No Change - Use 550 sec	DNA - No Change - Use 550 sec	DNA - No Change - Use 550 sec	548	364	351
	DCAS081	Normal Toasting, 8 slices at a time, 24 total		60	578	DNA - No Change - Use 518 sec	DNA - No Change - Use 518 sec	DNA - No Change - Use 518 sec	540	376	363
Nuisance - 3 Welding	DCAS089	Welding steel, 2.4 m below ceiling		66	540	DNA (3.86 at 522sec)	161	119	DNA (3.47 at 526sec)	291	169
	DCAS090	Welding steel, 2.4 m below ceiling	repeat of dcas089	80	900	DNA (6.08 at 738sec)	185	130	617	277	252
	DCAS091	Welding steel, 2.4 m below ceiling	repeat of dcas089	156	756	DNA (5.58 at 549sec)	138	117	465	151	130
Nuisance - 4 Cutting Steel with Acetylene Torch	DCAS085	Cutting steel with acetylene torch, 2.4 m below ceiling		75	397	DNA (.31 at 305sec)	DNA (.31 at 305sec)	DNA (.31 at 305sec)	16	8	8
	DCAS087	Cutting steel with acetylene torch, 2.4 m below ceiling	repeat of dcas085	150	465	DNA - No Change - Use 315 sec	DNA - No Change - Use 315 sec	DNA - No Change - Use 315 sec	129	66	62
	DCAS088	Cutting steel with acetylene torch, 2.4 m below ceiling	repeat of dcas085	65	430	DNA (4.13 at 386sec)	361	353	227	.9	9
Nuisance - 5 Grinding Steel	DCAS074	Grinding steel	Steel setup 2.4 m below ceiling	60	841	DNA (.89 at 725sec)	DNA (.89 at 725sec)	DNA (.89 at 725sec)	666	288	91
	DCAS082	Grinding steel	repeat of dcas074	60	620	DNA (.38 at 859sec)	DNA (.38 at 859sec)	DNA (.38 at 859sec)	DNA - Use 616 sec	DNA - Use 616 sec	DNA - Use 616 sec
Nuisance - 6 Grinding Cinder Block	DCAS083	Grinding cinder block, 2.4 m below ceiling		60	939	918	318	314	DNA - No Change - Use 879 sec	DNA - No Change - Use 879 sec	DNA - No Change - Use 879 sec
	DCAS084	Grinding cinder block, 2.4 m below ceiling	repeat of dcas083	60	750	926	922	536	DNA - No Change - Use 690 sec	DNA - No Change - Use 690 sec	DNA - No Change - Use 690 sec

Table 6. Summary of Tests conducted, organized by scenario

Source Type/ Scenario No./ Description	Test ID	Source Description	Comments	Ignition/ Start Tim (seconds	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec) 11 % obscuration per meter	Photoelectric Alarm Times (sec) 1.63 % obscuration per meter	Photoelectric Alarm Times (sec) 0.82 % obscuration per meter	Ionization Alarm Times (sec) 4.2 % obscuration per meter	Ionization Alarm Times (sec) 1.63 % obscuration per meter	Ionization Alarm Times (sec) 0.82 % obscuration per meter
Nuisance - 7 Cutting Lauan Board	DCAS092	Cutting lauan with circular saw		60	660	DNA (0.63 at 352sec)	DNA (0.63 at 352sec)	DNA (0.63 at 352sec)	DNA - Use 360 sec	DNA - Use 360 sec	DNA - Use 360 sec
	DCAS093	Cutting lauan with circular saw	repeat of dcas092, circuit breaker tripped unable to complete test	125	525	DNA (.63 at 391sec)	DNA (.63 at 391sec)	DNA (.63 at 391sec)	DNA - Use 97 sec	DNA - Use 97 sec	DNA - Use 97 sec
	DCAS094	Cutting lauan with circular saw	repeat of dcas092, mic pump not turned on	60	690	DNA (.56 at 68sec)	DNA (.56 at 66sec)	DNA (.56 at 68sec)	DNA - Use 322 sec	DNA - Use 322 sec	DNA - Use 322 sec
	DCAS095	Cutting lauan with circular saw	repeat of dcas092	60	495	DNA (.46 at 800sec)	DNA (.46 at 800sec)	DNA (.46 at 800sec)	DNA (-1.04 at 443sec)	DNA (-1.04 at 443sec)	DNA (-1.04 at 443sec)
Nuisance - 8 Burning Popcorn I Microwave	DCAS096	Burning popcorn in microwave		60	780	440	381	377	DNA - Use 461 sec	DNA - Use 461 sec	DNA - Use 461 sec
	DCAS097	Burning popcorn in microwave	repeat of dcas096	60	780	DNA (10.17 at 452sec)	389	376	DNA - Use 708 sec	DNA - Use 708 sec	DNA - Use 708 sec
	DCAS098	Burning popcorn in microwave	repeat of dcas096	60	780	422	401	397	DNA - Use 683 sec	DNA - Use 683 sec	DNA - Use 683 sec
Nuisance - 9 Gasoline Engine	DCAS139	Gas Engine		60	960	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA (.5 at 884sec)	DNA (.5 at 884sec)	DNA (.5 at 884sec)
	DCAS140	Gas Engine	repeat of dcas139	60	960	DNA - No Change - Use 900 sec	DNA - No Change - Use 660 sec	DNA - No Change - Use 360 sec	DNA - (1.13 at 70sec)	DNA - (1.13 at 70sec)	DNA - (1.13 at 70sec)
	DCAS141	Gas Engine	repeat of dcas139	60	960	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 540 sec	DNA - (.69 at 49sec)	DNA - (.69 at 49sec)	DNA - (.69 at 49sec)
Nuisance - 10 Electric Heater an Light	DCAS133	Electric heater, 1.5 m below ceiling		60	950	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec	DNA - No Change - Use 900 sec
	DCAS134	2 Electric heaters and 1 halogen worklight	units positioned 3.1 m from North wall and 1.5 m below ceiling	60	660	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 150 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 150 sec
	DCAS135	2 Electric heaters and 1 halogen worklight	repeat of dcas134	60	660	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 240 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 240 sec
Nuisance - 10 cont.	DCAS136	2 Electric heaters and 1 halogen worklight	repeat of dcas134	60	660	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 180 sec)	DNA - No Change - Use 600 sec	DNA - No Change - Use 600 sec	DNA - No Change - Use 180 sec)
Nuisance - 11 People Talking	DCAS137	People Talking, 5 people total		60	1260	DNA - No Change - Use 1200 sec)	DNA - No Change - Use 1200 sec)	DNA - No Change - Use 1200 sec)	DNA - No Change - Use 1200 sec)	DNA - No Change - Use 1200 sec)	DNA - No Change - Use 1200 sec)
	DCAS138	People Talking, 4 people total	repeat of dcas 137	60	2010	DNA - No Change - Use 1950 sec	DNA - No Change - Use 1950 sec	DNA - No Change - Use 1950 sec	DNA - No Change - Use 1950 sec	DNA - No Change - Use 1950 sec	DNA - No Change - Use 1950 sec

Table 6. Summary of Tests conducted, organized by scenario

Source Type/ Scenario No./ Description	Test ID	Source Description	Comments	Ignition/ Start Tim (seconds	Flame Out/Stop Time (seconds)	Photoelectric Alarm Times (sec)			Ionization Alarm Times (sec)		
						11 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter	4.2 % obscuration per meter	1.63 % obscuration per meter	0.82 % obscuration per meter
Nuisance - 12 Cigarette smokers	DCAS130	Smoking Cigarettes, 6 total		65	745	DNA (3.47 at 648sec)	585	292	DNA - Use 632 sec	DNA - Use 632 sec	DNA - Use 632 sec
	DCAS131	Smoking Cigarettes, 7 total		63	533	DNA (2.48 at 428sec)	122	105	DNA (.02 at 399sec)	DNA (.02 at 399sec)	DNA (.02 at 399sec)
	DCAS132	Smoking Cigarettes, 12 total		65	623	DNA (3.34 at 569sec)	305	116	DNA (.84 at 498sec)	DNA (.84 at 498sec)	485
	DCAS142	Smoking Cigarettes, 4 people, 12 cigarettes		60	890	DNA (8.29 at 792sec)	171	171	DNA (2.08 at 733sec)	670	381
	DCAS143	Smoking Cigarettes, 4 people, 14 cigarettes	repeat of dcas142	60	999	DNA (7.38 at 456sec)	154	99	DNA (2.45 at 892sec)	875	380
	DCAS144	Smoking Cigarettes, 4 people, 17 cigarettes	repeat of dcas142	60	976	DNA (5.03 at 769sec)	241	161	DNA (2.88 at 719sec)	312	308

Due to the incipient nature of the fire sources, both the photoelectric and ionization smoke detectors did not necessarily reach alarm levels during each fire test. For example, in the alcohol pool fires (see Table 6) the photoelectric detector did not measure a smoke level above any of the three alarm thresholds evaluated; the ionization detector reached alarm conditions for only the two lower alarm thresholds. If sufficient fuel was provided in the real fire source tests to allow the fires to grow beyond the incipient sizes tested, the smoke detectors would be expected to reach all three alarm levels. In cases where the detector did not achieve the specified alarm level, the entry in Tables 5 and 6 is denoted with 'DNA' for 'did not alarm.' In order to process these DNA cases in the analyses discussed in Section 5, the time at which the detector reached a maximum smoke level was noted. For tests in which the detector did not respond at all, the entry includes the comment 'DNA - No Change,' and a time is specified that corresponds to the time at which the greatest response was observed from the other sensors.

4.6.1 Sensor Test Data

The gas sensor calibrations were checked at the beginning of the test program and later at the completion of the tests. Calibration gases were certified mixtures of one or two gases in nitrogen. Appendix C contains details of the calibration gas mixtures. The mixes were chosen so as not to combine gases which could cause cross-interference with sensor responses based on manufacturer data. Table 7 shows the results of the sensor evaluations. The results are quite mixed. The O_2, $CO_{50\,ppm}$, $CO_{4000\,ppm}$, NO, CO_2 and HCN sensors maintained good performance throughout the test series. The H_2 sensor proved to be quite sensitive to temperature, with maximum fluctuations at ambient conditions of $\pm$18 ppm. Comparing the initial and final calibration measurements, the H_2 sensor drifted 14 percent low compared to the calibration value (175 ppm for a 200 ppm full-scale range). The NO_2 and ethylene (general hydrocarbon calibrated to ethylene) sensor calibrations decreased over the course of testing by 50 and 35 percent, respectively. The SO_2 sensor failed during the test series; the time is not known.

4.6.2 Baseline Performance of Conventional Smoke Detectors

Tables 8, 9 10 present summaries of the alarm responses of the Simplex photoelectric and ionization smoke detectors at the three alarm levels specified above. These levels represent typical alarm sensitivity of detectors in the field, the maximum sensitivity allowed by UL 268 (i.e., minimum alarm level) and twice the maximum sensitivity allowed by UL 268 (i.e., half the minimum alarm level). These tables establish the baseline performance against which candidate multi-signature detectors are compared. Each table corresponds to one of the three alarm levels. The tables present the number of tests for which an alarm occurred versus the number of tests conducted for each fire and nuisance source test scenario. The rows in bold indicate a total count of alarms versus the total number of tests conducted. From these totals, the percent correct classification can be calculated, where a correct classification is when a detector alarms for a fire event and a detector does not alarm for a nuisance source event.

Table 7. Gas Sensor Test Data

Sensor	Calibration Gas Concentration	Initial Measurement	Final Measurement
O_2	Ambient air 17.2%	21.1% NA	21.4% 17.4%
$CO_{50\ ppm}$ (mA)	45 ppm 10.7	NA 10 ppm	42 ppm 10.7
H_2	175 ppm	175 ppm	151 ppm
NO_2	4.46 ppm	4.5 ppm	2.2 ppm
$CO_{4000\ ppm}$ (mV)	870 ppm 10.7 ppm	NA 11 ppm	929 ppm 9.5 ppm
H_2S	4.52 ppm	No reaction	-0.1 ppm
NO	18 ppm	18.2 ppm	18.1 ppm
HCl	8.45 ppm	-1 ppm, consistently negative result	-1.2 ppm
SO_2	9.0 ppm	9.0 ppm	0 ppm
CO_2	2000 ppm	1986 ppm	2080 ppm
HCl	24.8 ppm	25 ppm	24.9 ppm
Ethylene	45.4 ppm	45.4 ppm	29.3 ppm

Notes:

-NO, H_2, SO_2 sensors were re-calibrated at the beginning of the test series following instructions from City Technology. The remaining sensors were used or received.

-SO_2 sensor failed during test series.

-H_2S sensor did not react to the calibration gas. It was exposed to H_2S gas created at NRL and reacted well. Calibration gas was suspect.

-HCL sensor did not respond to the calibration gas, although it did respond in some of the fire tests. Lack of response to the calibration gas may have been due to problems with the cal gas or due to difficulties in avoiding HCL dropout in the sampling train used during calibration. The HCL cal gas did not maintain specification based on testing at NRL. Teflon tubing and flow meters were used in the sample train to avoid HCL dropout.

Table 8. Summary of Alarm Response of Conventional Smoke Detectors at Typical Alarm Levels

Source	Photoelectric - 11% Obs./m	Ionization - 4.2% Obs./m
Real Alarm		
Propane Burner	0/7	0/7
Heptane pool fire	0/7	7/7
JP-5 pool fire	5/5	5/5
JP-8 pool fire	2/2	2/2
Alcohol pool fire	0/4	0/4
Smoldering mattress	3/3	2/3
Flaming mattress (foam only)	0/1	1/1
Flaming mattress (loose bedding)	1/4	1/4
Flaming mattress (tucked bedding)	1/3	3/3
Smoldering pillow	2/4	2/4
Laundry pile fire	1/3	3/3
Smoldering electrical cable (LSDSGU-14)	3/3	1/3
Smoldering electrical cable (LSTHOF-9)	3/3	1/3
Smoldering electrical cable (LSTPNW-1 ½)	2/3	0/3
Flaming electrical cable (LSDSGU-14)	3/3	3/3
Flaming electrical cable (LSTHOF-9)	0/3	3/3
Flaming electrical cable (LSDSGU-50)	0/1	0/1
Office Trash Can fire	2/5	5/5
Pipe insulation (NH Armaflex) fire	0/3	4/4
Pipe insulation coated with oil fire (NH Armaflex)	0/3	3/3
Pipe insulation (Calcium silicate) fire	0/3	1/3
Pipe insulation coated with oil fire (Calcium silicate)	0/3	3/3
Polyimide acoustic insulation	3/4	4/4
Nomex honeycomb panel (TODCO)	3/4	4/4
Nomex honeycomb panel (Hexcel)	0/2	2/2
Acoustical insulation without face cloth	0/1	0/1
No. Detected/No. of Tests	**34/88**	**62/88**

Table 8. Summary of Alarm Response of Conventional Smoke Detectors at Typical Alarm Levels (Continued)

Source	Photoelectric - 11% Obs./m	Ionization - 4.2% Obs./m
Nuisance Alarms		
Burning toast	3/3	3/3
Normal toasting	0/3	2/3
Welding	0/3	2/3
Cutting steel with acetylene torch	0/3	3/3
Grinding steel	0/2	1/2
Grinding cinder block	2/2	0/2
Cutting lauan board	0/3	0/4
Burning popcorn in microwave	2/3	0/3
Gasoline engine exhaust	0/3	0/3
Electric heater and halogen lamps	0/4	0/4
People talking	0/2	0/2
Cigarette smokers	0/6	0/6
No. Detected/No. of Tests	**7/38**	**11/38**

Table 9. Summary of Alarm Response of Conventional Smoke Detectors at the Minimum UL 268 Alarm Level

Source	Photoelectric - 1.63% Obs./m	Ionization - 1.63% Obs./m
Real Alarm		
Propane Burner	0/7	0/7
Heptane pool fire	7/7	7/7
JP-5 pool fire	5/5	5/5
JP-8 pool fire	2/2	2/2
Alcohol pool fire	0/4	3/4
Smoldering mattress	3/3	3/3
Flaming mattress (foam only)	0/1	1/1
Flaming mattress (loose bedding)	2/4	4/4
Flaming mattress (tucked bedding)	2/3	3/3
Smoldering pillow	3/4	2/4
Laundry pile fire	1/3	3/3
Smoldering electrical cable (LSDSGU-14)	3/3	2/3
Smoldering electrical cable (LSTHOF-9)	3/3	3/3
Smoldering electrical cable (LSTPNW-1 ½)	3/3	0/3
Flaming electrical cable (LSDSGU-14)	3/3	3/3
Flaming electrical cable (LSTHOF-9)	3/3	3/3
Flaming electrical cable (LSDSGU-50)	1/1	0/1
Office Trash Can fire	5/5	5/5
Pipe insulation (NH Armaflex) fire	0/4	4/4
Pipe insulation coated with oil fire (NH Armaflex)	3/3	3/3
Pipe insulation (Calcium silicate) fire	1/3	3/3
Pipe insulation coated with oil fire (Calcium silicate)	3/3	3/3
Reiley Benton insulation	4/4	4/4
Acoustical insulation	0/1	0/1
Nomex honeycomb panel (TODCO)	4/4	4/4
Nomex honeycomb panel (Hexcel)	1/2	2/2
No. Detected/No. of Tests	**62/88**	**72/88**

Table 9. Summary of Alarm Response of Conventional Smoke Detectors at the Minimum UL 268 Alarm Level (Continued)

Source	Photoelectric - 1.63% Obs./m	Ionization - 1.63% Obs./m
Nuisance Alarms		
Burning toast	3/3	3/3
Normal toasting	0/3	2/3
Welding	3/3	3/3
Cutting steel with acetylene torch	1/3	3/3
Grinding steel	0/2	1/2
Grinding cinder block	2/2	0/2
Cutting lauan board	0/4	0/4
Burning popcorn in microwave	3/3	0/3
Gasoline engine exhaust	0/3	0/3
Electric heater and halogen lamps	0/4	0/4
People talking	0/2	0/2
Cigarette smokers	6/6	3/6
No. Detected/No. of Tests	**18/38**	**15/38**

Table 10. Summary of Alarm Response of Conventional Smoke Detectors at Half of the Minimum UL 268 Alarm Level

Source	Photoelectric - 0.82% Obs./m	Ionization - 0.82% Obs./m
Real Alarm		
Propane Burner	0/7	0/7
Heptane pool fire	7/7	7/7
JP-5 pool fire	5/5	5/5
JP-8 pool fire	2/2	2/2
Alcohol pool fire	0/4	4/4
Smoldering mattress	3/3	3/3
Flaming mattress (foam only)	0/1	1/1
Flaming mattress (loose bedding)	2/4	4/4
Flaming mattress (tucked bedding)	2/3	3/3
Smoldering pillow	3/4	2/4
Laundry pile fire	1/3	3/3
Smoldering electrical cable (LSDSGU-14)	3/3	2/3
Smoldering electrical cable (LSTHOF-9)	3/3	3/3
Smoldering electrical cable (LSTPNW-1 ½)	3/3	0/3
Flaming electrical cable (LSDSGU-14)	3/3	3/3
Flaming electrical cable (LSTHOF-9)	3/3	3/3
Flaming electrical cable (LSDSGU-50)	1/1	1/1
Office Trash Can fire	5/5	5/5
Pipe insulation (NH Armaflex) fire	1/4	4/4
Pipe insulation coated with oil fire (NH Armaflex)	3/3	3/3
Pipe insulation (Calcium silicate) fire	2/3	3/3
Pipe insulation coated with oil fire (Calcium silicate)	3/3	3/3
Reiley Benton insulation	4/4	4/4
Acoustical insulation	0/1	1/1
Nomex honeycomb panel (TODCO)	4/4	4/4
Nomex honeycomb panel (Hexcel)	1/2	2/2
No. Detected/No. of Tests	**64/88**	**75/88**

Table 10. Summary of Alarm Response of Conventional Smoke Detectors at Half of the Minimum UL 268 Alarm Level (Continued)

Source	Photoelectric - 0.82% Obs./m	Ionization - 0.82% Obs./m
Nuisance Alarms		
Burning toast	3/3	3/3
Normal toasting	0/3	2/3
Welding	3/3	3/3
Cutting steel with acetylene torch	1/3	3/3
Grinding steel	0/2	1/2
Grinding cinder block	2/2	0/2
Cutting lauan board	0/4	0/4
Burning popcorn in microwave	[illegible]/3	0/3
Gasoline engine exhaust	0/3	0/3
Electric heater and halogen lamps	0/4	0/4
People talking	0/2	0/2
Cigarette smokers	6/6	4/6
No. Detected/No. of Tests	**18/38**	**16/38**

Using the percent correct classification, the overall performance of the smoke detectors for each alarm level has been summarized in Table 11. These values are used as the baseline comparison for the multivariate classification schemes presented in Section 5.3. For a number of the fire scenarios (e.g., heptane, alcohol, pipe insulation (calcium silicate) fire), decreasing the alarm level (increasing sensitivity) resulted in more alarms and, thus, higher percent correct classification for fires. However, the better performance with respect to fire sources is offset with poorer performance in correctly classifying nuisance sources (i.e., not alarming for a nuisance source event). For example, the photoelectric detector set at an alarm level of 11% Obs./m correctly classified 82 percent of the nuisance source tests (i.e., the detector did not reach the alarm level). However, at the lower alarm levels (1.63% and 0.82% Obs./m), the photoelectric detector only classified 53 percent of the nuisance sources correctly. In other words, with the decrease in the alarm level, the nuisance alarm rate increased from 18 percent to 47 percent.

Table 11. Summary of Smoke Detector Performance Based on Percent Correct Classification

	Photoelectric			Ionization		
Alarm Level (% Obs./m)	Fire Source	Nuisance Source	Overall[1]	Fire Source	Nuisance Source	Overall
Typical: 11 (Photo) 4.2 (Ion)	39%	82%	51% (76%)	70%	71%	71% (85%)
UL 268 Minimum: 1.63	70%	53%	65% (83%)	82%	61%	75% (88%)
Half the UL 268 Minimum: 0.82	73%	53%	67% (83%)	85%	58%	77% (88%)

[1] - Overall percent correct is based on 88 fires and 38 nuisance sources (126 total events). The parenthetical value is the percent correct based on 88 fires, 38 nuisance sources and 126 nonfire (backgound) events. The parenthetical value is the overall classification parameter which can be compared to the multivariate analysis results in Section 5.3.

One point should be considered in this study as well as any fire detection study; that is the definition of a real fire event and a nuisance source event is dependent on the application. For instance, certain fires, such as a propane burner, may be considered an acceptable controlled fire phenomena for laboratory or shop use. In this case, the propane burner would be considered a nuisance source. However, in other applications where early warning detection is required, the propane burner is representative of an incipient fire which should be detectable by the fire detection system. In this test program, the propane burner sources were considered as incipient fires in order to evaluate the potential sensitivity of candidate multi-signature alarm algorithms compared to the conventional smoke detectors.

Although the propane burner was considered a fire event, other controlled combustion events were identified as nuisance sources. An example is cutting metal with an acetylene torch. One of the greatest difficulties of developing a fire detection system is being able to discriminate between desired and undesired fire events, besides the obvious nuisance and real fire alarm sources. This point is raised as a consideration when evaluating the performance of both conventional smoke detectors and multi-signature alarm algorithms. Ultimately, criteria will need to be established by the Navy for the minimum detectable fire size and the need for early warning detection balanced by acceptable nuisance alarm frequency.

The variable interpretation of combustion sources as either real fire or nuisance events is an issue which can be effectively handled by multivariate detection schemes. The use of classification techniques with fuzzy logic can be made to recognize the same combustion source as either a real fire or a nuisance source dependent on the space. The alarm algorithms can easily be made compartment specific by simply adjusting the software and applying apriori rules based on the space and possible sources. The initial work presented in this report focuses on developing a single alarm algorithm to be used in all ship applications; however, for best effectiveness, the final detection system may be compartment specific.

5.0 DATA ANALYSIS

In this program, data analysis refers to the analytical tasks performed to identify candidate signatures and alarm algorithms. This work involves three main tasks: 1) initial data processing, 2) univariate data analysis and 3) multivariate data analysis. The initial data processing prepared the test data for use in both the univariate and multivariate analyses. Each of the tasks is discussed below.

5.1 Initial Data Processing

The raw data for all sensors were directly converted into engineering units, such that gas concentrations were recorded as parts per million (ppm), except for oxygen which was recorded as percent by volume. Smoke measurements were recorded as percent obscuration per meter, except for the output from the MIC and the residential ionization detector which were dimensionless. Temperatures were recorded as degrees Celsius and the relative humidity was recorded as percent RH.

The ambient value for each of the sensors was calculated as the average value for the 60 seconds prior to source initiation. For the ODM and UL 217 optical detector the average ambient values were used in Equation 1 as I_o to calculate the sensor output as percent obscuration per meter. The commercial ionization and photoelectric smoke detection system uses processing technology that accounts for the ambient smoke level in calculating the alarm condition.

The univariate analyses performed in this study used sensor measurements reported as changes above ambient conditions. The data were converted to changes from ambient by subtracting the average ambient value from each data point. Signature data was also evaluated (univariate analysis) in terms of rate of rise of the value. The multivariate analyses used processed data which was not adjusted for the ambient condition; this allowed three different event classification categories of non-fire (ambient conditions), fire and nuisance source. In performing the multivariate analyses, there were advantages of having a large number of non-fire events besides nuisance sources. One reason is that an actual detector will experience general background variations over the majority of its active life compared to either isolated fire or nuisance sources.

5.1.1 Smoke Detector Alarm Thresholds as Criteria for Comparison

One objective of performing the data analysis was to assure that all sensor outputs (signatures) were compared on an equivalent basis (i.e., signatures occurring at the same time). Comparing peak or steady-state signal levels was not used since this leads to processing data that are measured at different times and, thus, is not applicable to a real-time detection system. Instead, data were compared at distinct times corresponding to the response time of conventional ionization and photoelectric detectors set to alarm at three different settings: A) typical alarm threshold of conventional detectors (4.2% Obs./m for ionization detectors and 11.0% Obs./m for photoelectric detectors [5]), B) The minimum alarm level allowed by UL Standard 268 (1.63% Obs./m) and C) half the value of the minimum setting (0.82% Obs./m). This method of comparing signatures at particular times corresponding to very sensitive alarm levels, provides a means of identifying parameters with respect to a practical benchmark. As presented in Section 4.4, alarm times for each of the three alarm thresholds were calculated for the photoelectric and ionization detectors, defining six different data sets.

A detector was considered to have reached an alarm condition when the detector exceeded the specified threshold for 3 consecutive time steps (12-15 seconds). The time of the first of the 3 time steps was used as the alarm time. Using the first time step was conservative in that it provides the fastest response time for the conventional detectors to which to compare the performance of candidate multi-signature alarm algorithms. In reality, some detection systems use delays for alarm verification. In these cases, the fire detection performance of the multi-signature alarm algorithms would be better than reported.

5.1.2 Consideration of Sensor Response Time

Sensor measurements were not corrected for individual sensor response times. Since all sensor measurements were *situ* and the sensors had typical or fast response times compared to available technology, the data uncorrected for response time was most representative of signature patterns that would be measured by a practical multi-signature fire detector based on available technology. The implications of this approach is discussed further in Section 6.

5.1.3 Data Processing

As noted above, six data sets were developed based on time intervals corresponding to the response time of conventional ionization and photoelectric detectors set to alarm at three different settings (i.e., three alarm criteria for each of two detectors). The times corresponding to the different alarm thresholds are presented in Table 5 and 6 for each test. At each smoke alarm threshold criteria, the sensor data were characterized by two values: 1) change from ambient conditions and 2) rate of rise of the signature.

Several techniques were used to remove noise from the transient data, in order to obtained the most accurate values as possible at the discrete alarm threshold times. The techniques used removed noise while preserving the character of the data (i.e., peak values). First, the sensor data were integrated in time to yield a running summation of the value. The integrated data were then smoothed using a least squares smoothing routine (Savitzky-Golay) commonly used in analytical chemistry applications, such as chromatography [6]. The Savitzky-Golay routine [6] is a smoothing filter that bases the estimation for the smoothed data point on a linear regression using the actual local data points on either side of the point to be estimated. A twenty five point regression was shown to adequately reduce noise while also preserving the data. The derivative of the regression function at the alarm threshold time yielded the value of the smoothed sensor data and the second derivative yielded the rate of rise value. All sensor data, except for the commercial photoelectric and ionization smoke detectors, were processed as described above. The Simplex smoke detector data were not smoothed since the independent data acquisition system for these detectors maintained good signal quality.

All calculations were performed using Excel worksheets and macros written in Visual Basic. The Excel program automatically developed the six data sets into tables of the form shown in Table 12. These tables were quite large, including 126 tests (rows) and 46 columns of sensor data (23 sensors, 2 values).

Table 12. Example of Processed Data Set

Source No.	Test No.	Alarm Time (sec)	Sensor 1		Sensor 2		*Continues to...*		Sensor N	
			Value	Rate of Rise	Value	Rate of Rise			Value	Rate of Rise
Real 1										
Real 2										
Continues to...										
Real 26										
Nuisance 1										
Nuisance 2										
Continues to...										
Nuisance 12										

5.2 Univariate Analysis

The goal of the univariate data analysis was to provide a first cut evaluation of the sensors in order to identify which may have value as independent signatures. A candidate signature should indicate a statistically significant degree of discrimination between the real fire scenarios and the nuisance source scenarios. These candidate signatures would potentially be useful in a multi-criteria alarm algorithm which is a voting type algorithm. The univariate analysis identified the candidate sensors that show discrimination between real and nuisance events based on the discrete data sets corresponding to different smoke detector alarm levels.

It is important to note that this data is effectively independent of time. The elapsed time of the test, or the time dependency of an individual sensor is not accounted for in this analysis. Although the rate of change of a sensors response was recorded at discrete times, the sequential nature of the sensors response cannot be characterized in this type of univariate analysis. Only inferences about the average sensor response to real and nuisance events at the six data set times can be made.

5.2.1 Approach

The first step of the analysis was to obtain a set of descriptive statistics for each sensor channel for both the real and nuisance events. These statistics included the mean, minimum and maximum values, median value, the 95% confidence interval and the variance for each sensor at a given alarm threshold. All analyses discussed in this section were performed using the computational statistical package SYSTAT [7] on a personal computer. Calculation of these basic descriptive statistics and a cursory trend analysis is a standard first step when analyzing a large amount of data. Examining the mean sensor values for both real and nuisance events eliminated sensors that had the same mean during both events. These sensors were determined not to be able to discriminate real from nuisance events. The variance of the data for a given sensor was also an indication of discrimination. Variance describes the distribution of data about a mean. If the distribution of real and nuisance event data overlapped significantly for a sensor, the ability of the sensor to discriminate the events is impaired.

Sensors that appeared to have different mean values were further analyzed. The significance of the difference between the nuisance and real average values was determined by an analysis of variance (ANOVA). This is a standard statistical test that examines two mean values from two sample populations, in this case, the mean value for a given sensor for all nuisance events and all fire events. This type of analysis reduces the influences of uncontrolled parameters in an experiment. An ANOVA is robust and relatively insensitive to non-normal distributions of the data and different variances among parameter distributions in a data set [8]. An ANOVA uses a linear regression type analysis to determine the effect a parameter has on a calculated mean value. A sensor was determined to discriminate real from nuisance events if the mean values were significantly different for each scenario. The calculations used the data sets described in Section 5.1 except the tests which did not reach the specified alarm level were

excluded (i.e., if a test did not result in a photoelectric value of 1.63% Obs./m or higher, it was not included in the analysis for the 1.63% alarm threshold data set). These tests were excluded to avoid skewing the data.

The ANOVA test was used to determine a significant difference between mean values. This study has two mean values of importance, a sensors mean value during a real fire and the mean value during a nuisance event. Inferences about the difference in the mean sensor values during these two events are based on a comparison of two independent measures of variance of the data [8]. The first measure of variance is estimated from the overall samples means. In this study the overall sample means are calculated from each sensor value reported for a given data set during all real and nuisance events. A second measure of variance is then estimated from the mean values of the samples for each event (real or nuisance). The analysis assumes that if the population means are equal (a sensor cannot discriminate) a comparison of the estimated variance measures will show this (using the F distribution and predetermined level of significance).

The two sample variances calculated are independent estimates of the overall population variance, and because of this, are assumed to have an F distribution [8]. Using well developed statistical tables, a hypothesis test is done to determine the level of significance in the two mean values based on the variances. This study used a 95% confidence requirement for significance for discrimination.

The criteria used to determine sensor discrimination were:

The mean sensor value: for both real and nuisance events with their respective standard errors (standard errors take into account the sample size to reduce the error associated with a mean estimate, the sample error is smaller than the standard deviation)

The probability statistic (p): a value taken from statistical tables that corresponds directly to the F-Ratio value and the degrees of freedom. The p value will be 0.05 to determine significance for this analysis (95% significance).

A candidate sensor was determined to have a significant difference between its fire and nuisance source events when the reported averages for each event met the following criteria: 1) The reported probability statistic was less than 0.05, indicating a significant difference in the means at the 95% confidence level. 2) The distribution of the data at the 95% confidence interval did not overlap extensively.

As with the multivariate analyses, the photoelectric alarm threshold data sets were used in this analysis. The data sets based on the photoelectric alarms were chosen because photoelectric smoke detectors are much more widely used in commercial detection systems. Additionally, the photoelectric alarm levels span a larger range of smoke levels (11 to 0.82% Obs./m) than the ionization alarm levels (4.52 to 0.82% Obs./m).

5.2.2 Results

Tables 13 and 14 detail the sensors that were identified as providing useful information in discerning between real and nuisance events for two of the photo alarm level data sets. The complete results for all sensors are included in Appendix D. The results show that rate of rise values provide significant discrimination, indicating that a temporal analysis may reveal additional information of key signature patterns. The trend between the temperature sensor real alarm mean and nuisance source mean was not expected (Table 13). The mean value for the nuisance events was greater than for the real fire events. The temperature nuisance event mean is influenced mainly by the gasoline engine exhaust and electric heater/halogen lamp tests. If these specific events are not included in the mean, the temperature sensors are not identified as good discriminators.

The MICX (measuring ionization chamber) and ION (Simplex commercial ionization detector) sensors show good discrimination capability based on the separation of the means with respect to the standard error. Tables 13 and 14 also indicate that the residential ionization (RION) detector provides good discrimination potential. These results indicate that a smoke sensor based on the ionization principle could be a key element in a multi-signature fire detector. Carbon monoxide is identified at both alarm levels as a good discriminating signature.

A limitation of this analysis is that it cannot be used directly to identify sensor combinations for a multi-signature detection system. Even if a sensor does not have significant differences between mean values for real and nuisance sources, this does not imply that the sensor has no value in a multi-sensor detection system. For instance, the sensor may provide useful information to differentiate several key nuisance alarm sources.

Table 13. Discriminating Sensor Signals at Photoelectric 1.63% Alarm Threshold

Data Channel (Sensor)	**Mean Value with 95% Confidence Interval**		**Probability Statistic**
	Real Fire Event n=59	**Nuisance Event n=38**	
MICX (volts)	0.375 ± 0.050	0.179 ± 0.064	0.000
RION Rate of Change (Volts/sec)	0.010 ± 0.002	0.002 ± 0.004	0.000
ION (Volts)	3.288 ± 0.772	1.218 ± 0.964	0.001
Photoelectric (% obscuration per meter)	2.768 ± 0.644	1.197 ±0.401	0.003
$CO_{50\ ppm}$ Rate of Change (ppm/sec)	0.174 ± 0.074	0.015 ± 0.092	0.008
CO_2 Rate of Change (ppm/sec)	1.430 ± 0.452	0.674 ± 0.562	0.039
HCN (ppm)	0.229 ± 0.110	0.050 ± 0.136	0.043
RION (Volts)	0.586 ± 0.154	0.334 ± 0.192	0.043
$CO_{4000\ ppm}$ Rate of Change (ppm/sec)	0.164 ± 0.086	0.022 ± 0.011	0.044
HCL Rate of Change (ppm/sec)	0.013 ± 0.006	0.003 ± 0.008	0.049
Temperature - Omega (°C)	0.305 ± 0.388	1.203 ± 0.484	0.005

Table 14. Discriminating Sensor Signals at Photoelectric 11% Alarm Threshold

Data Channel (Sensor)	Mean Value with 95% Confidence Interval		Probability Statistic
	Real Fire Event n=36	Nuisance Event n=38	
$CO_{50\,ppm}$ (ppm)	19.022 ± 4.360	6.921 ± 2.244	0.000
MICX (volts)	0.483 ± 0.070	0.205 ± 0.068	0.000
ION (Volts)	5.606 ± 1.188	1.626 ± 1.158	0.000
Photoelectric (% obscuration per meter)	12.411 ± 1.392	4.282 ± 1.354	0.000
RION (Volts)	1.083 ± 0.264	0.429 ± 0.256	0.001
ODM (% obscuration per meter)	25.628 ± 6.442	10.821 ± 6.270	0.002
SO_2 (ppm)	0.328 ± 0.140	0.013 ± 0.138	0.002
HCL (ppm)	2.325 ± 0.678	0.918 ± 0.660	0.004
RION Rate of Change (Volts/sec)	0.010 ± 0.004	0.002 ± 0.004	0.007
Ethylene (ppm)	17.047 ± 2.306	10.411 ± 3.802	0.017
HCN (ppm)	0.722 ± 0.406	0.071 ± 0.394	0.024
HCL Rate of Change (ppm/sec)	0.014 ± 0.008	0.003 ± 0.008	0.038
$CO_{50\,ppm}$ Rate of Change (ppm/sec)	0.142 ± 0.088	0.014 ± 0.086	0.041
H_2S Rate of Change (ppm/sec)	0.004 ± 0.002	0.001 ± 0.002	0.048

5.3 Multivariate Analysis

5.3.1 Introduction

Multivariate classification or pattern recognition techniques, as applied to sensor data for fire detection, can be described as follows. The sensors encode chemical information about a fire in a numerical form. Each sensor defines an axis in a multidimensional space as shown in Figure 2. Events such as fires and nuisance sources can be represented as points (A, B, or C) positioned in this space according to sensor responses. If the sensors are chosen appropriately, similar events will tend to cluster near one another in space. Multivariate statistics and numerical analysis methods are used to investigate such clustering to elucidate relationships in multidimensional data sets without human bias. In addition, multivariate classification methods, define as mathematical functions the boundaries between the classes, so that a class of interest can be identified from other events. Application of the these methods can be used to reduce false alarm rates and provide for early fire detection.

Sensor arrays consisting of several sensors measuring different parameters of the environment produce a pattern or response fingerprint. Multivariate data analysis methods can be trained to recognize the pattern of an important event such as a fire and can be very powerful for detection. It is not practical for a sensor system to have an infinite number of sensors because the costs associated with maintenance and calibration can be staggering. It is not useful to have sensors that are highly correlated in an array because they do not contribute new information or

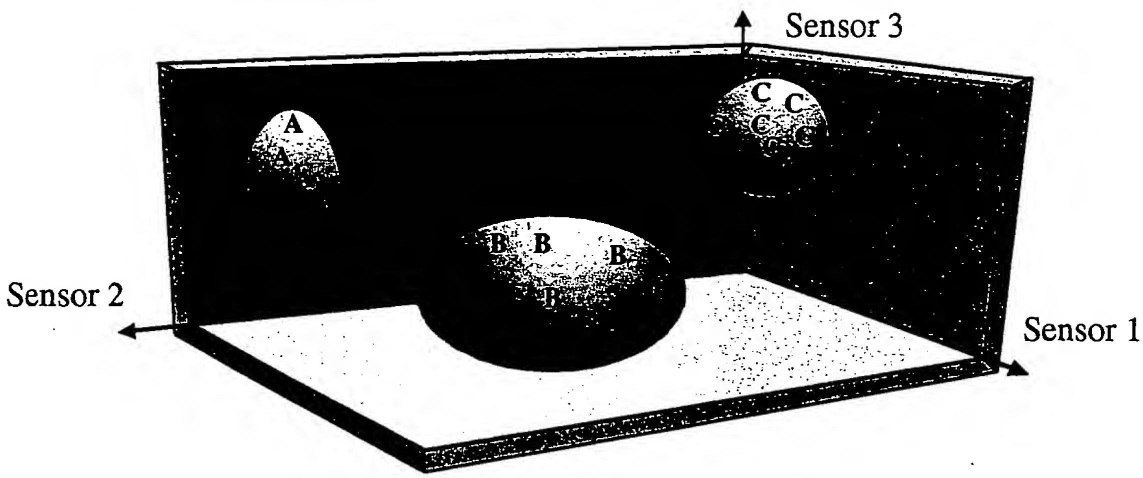

Fig. 2 – Conceptual picture of a pattern space consisting of a three-sensor array and three classes of events. Class A could be nonfire or baseline events, Class B could be different types of fires and Class C could be nuisance sources.

unique information to the analysis. Although when building a system for real world use, some redundancy or overlapping information is necessary for system reliability in the case of a point failure. Therefore, sensors used in arrays and for sensor fusion need to be selected intelligently.

Exploratory algorithms are designed to reduce large complex data sets into interpretable views that show the natural groupings of the data and can show which variables or sensors most strongly influence the patterns or signatures. A very effective approach to the selection of sensors is by applying cluster analysis. The sensor responses to events and nonevents are investigated using these methods. These are data driven techniques that look for relationships within the data; thus allowing for the determination of the best sensors for a particular application based on the sensor responses. Cluster analysis or unsupervised learning methods can be used to determine the sensors contributing to the maximum variation in the data space. The output of these algorithms ranks the sensors according to their contribution and combine sensors that are similar. The results of these methods allow one to select the appropriate number and type of sensors to be used. These techniques can also be used to elucidate the underlying parameters that correlate with the fire event.

Multivariate classification methods are used to identify a fire and to discriminate fires from nonfires and nuisance sources. Classification relies on the comparison of fire events with nonfire events. These methods are considered supervised learning methods because they give both the sensor responses and correct classification of the events. Variations in the responses of sensors can be used to train an algorithm to recognize fire events when they occur. A key to the success of these methods is the appropriate design of sensor arrays. The event is important, but the ability to recognize an event requires knowledge of a nonevent. Good experimental design requires data sets that balance events with nonevents and provide maximum information with minimal experimentation.

Detection systems used for Damage Control automation have a very difficult environment in which to function since many events are occurring and most will not lead to a fire. Techniques such as matched filters (i.e., using a library look-up table) would not be useful in the complex shipboard environment. It is important to train the data analysis system to recognize events of interest as quickly and accurately as possible. The number of possible analyses and event scenarios is staggering. The issue becomes not only one of which analyses to search for in a chemical detection system, but also at what concentrations and which combinations of analysis concentrations can be used as a positive indication of a target event.

The classifier used in this study is a Probabilistic Neural Network (PNN) [9] that was developed at the Naval Research Laboratory for chemical sensor arrays. The analysis algorithms described in this paper evaluate discrete samples and develop classification models that examine individual chemical signatures at discrete points. It is expected that samples such as fire ignitions actually exist as a complex mixture of vapors with concentration gradients extending out away from the actual source. A new classification model is envisioned that will consider the spatial and temporal gradients and will be able to use all the valuable information available. The Gradient

Pattern Recognition method would consider accumulated evidence of chemical signatures over a broad geographical area, and would assume that within a given spatial region samples can be related and when taken together provide a stronger confidence level. Development of Gradient Pattern Recognition methods will be the subject of future work. This paper is to serve as a benchmark to compare discrete methods with temporal and spatial approaches.

In this study, a large database consisting of the responses of 23 sensors to several different types of fires and nuisance sources was generated and analyzed using a variety of multivariate methods. The objectives were two-fold. First, sufficient data was to be gathered to investigate and identify the types of sensors that would be useful in a sensor array for early warning fire detection. Pattern recognition methods assisted in this effort by clustering fires and nuisance sources with similar response patterns and by identifying similarities between the sensors. The second objective was to determine the ability of the probabilistic classifier in conjunction with chemical sensors to discriminate between nonfires, fires and nuisance sources. Such discrimination is necessary for an array detector to be practical and effective as a fire detection system.

5.3.2 Algorithm Development and Methodology

The database discussed in Section 5.1 was used in two ways, and described in this report as Parts I and II. The initial studies, Part I, were conducted on data from entire fire and nuisance source tests including about 1 minute of background, source ignition/initiation, source progression (varying lengths for different tests), termination and compartment venting (return to baseline). The Part I study was performed during the experimental program, and therefore the entire database was not available. This Part I data set of 20 sensors consisted of 64 different tests representing 14 different types of fires (40 tests) and 8 different nuisance sources (24 tests). These responses formed a 37635 X 20 data matrix (37635 represents the one second time step data of all 64 tests). Each row in the matrix is a pattern vector, representing responses of the 20 sensors to a given source at a given point in time. Table 15 shows the types of fires and nuisance sources used in this data set. Table 16 lists the sensor outputs used; all sensors were used except for the Simplex ionization and photoelectric detectors which had not been processed at the time of this initial study.

Table 15. Subset of Fires and Nuisance Sources used in Part I

Source Group	Source Group	Nuisance Source Group
Flaming Mattress (foam only)	Heptane	Burning Toast
Flaming Mattress (loose bedding)	JP-5	Normal Toasting
Smoldering Pillow	JP-8	Burning Popcorn
Laundry Pile	Alcohol	Cutting Lauan
Polyimide Acoustic Insulation	Smoldering Mattress	Welding
TODCO Wall Panel	Propane Burner/Marinite	Cutting Steel with Torch
Hexcel Wall Panel		Grinding Concrete
Propane Burner		Grinding Steel

Table 16. Subset of Sensors used in Part I

HCN (ppm)	H_2S (ppm)	Relative Humidity (%)
CO_2 (ppm)	SO_2 (ppm)	MIC X (V)
O_2 (%)	NO (ppm)	MIC Y (V)
CO (50 ppm)	NO_2 (ppm)	MIC Y20 (V)
CO (4000 ppm)	Ethylene (ppm)	ODM (V)
H_2 (ppm)	Temperature Omega (°C)	RION (V)
HCl (ppm)	Thermocouple TC (°C)	

In Part II, three data matrices were developed at discrete times corresponding to the different alarm levels of the photoelectric smoke detector (Section 5.1). The alarm times represent 0.82%, 1.63% and 11% obscuration per meter. The data sets were organized into three classes representing the sensor responses for baseline (nonfire), fires and nuisance sources. The baseline data represented the average of the initial 60 s of background data for each fire and nuisance source test (126 tests). The responses of the 22 sensors (all but the UL 217 Photo, which had been incorporated in only the later tests) for all the fire and nuisance source tests formed a 252 X 22 data matrix for each alarm level (252 = 126 baseline events, 88 fires and 38 nuisance source tests). The PNN classifier was trained to discriminate the three classes. Subsets of the original 252 X 22 matrices using different combinations of sensors were evaluated to determine which sensors contribute to the best classification results.

These data were analyzed on a PC using routines written in MATLAB, version 5.2 (Mathworks, Inc., Natick, MA). Many of the routines were implemented using the PLS_toolbox, version 2.0c (Eigenvector Technologies, Inc., Manson, WA). All the matrices were autoscaled[1]. The linear correlation between sensors was examined for each data set by calculating the correlation matrix. The data sets were studied using display and mapping routines, cluster analysis and PNN classification [9, 10, 11].

One of the most useful first steps in multivariate analysis is to observe the clustering of the data in the multi-dimensional space. Because it is impossible to imagine the data points clustering in n-dimensional space, display, mapping and cluster analyses are used. Three exploratory algorithms were used in this study to provide an interpretable view of the multi-

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[1] Sensor responses measure different parameters and contain numerical values of different magnitudes. It is important that large values such as temperature do not have a greater influence on the analysis than a sensor measuring a low concentration such as carbon monoxide. Each column in the data matrix containing the responses for an individual sensor was autoscaled to a mean of zero and a standard deviation of unity. Although autoscaling alters the actual values of the sensor responses, it does not alter the number of features or the basic geometry of the clustering.
Reference: Stuper, A.J., W.E. Brugger, and P.C. Jurs, *Computer Assisted Studies of Chemical Structure and Biological Function*, Wiley-Science: New York, 1979.

dimensional data space. These algorithms included principle component analysis, hierarchical cluster analysis and correlation matrix. Principal Component Analysis (PCA), also known as the Karhunen-Loeve transformation, is a display method that transforms the data into two- and three-dimensional space for easier visualization. PCA finds the axes in the data space that account for the major portion of the variance while maintaining the least amount of error. The three-dimensional example is shown in Figure 3. PCA finds the linear combinations of variables or sensors that describe the major trends in the data. The first principal component captures the largest amount of information or variance in the data. The best plane that represents the data space is achieved by plotting the first two principal components. Mathematically, PCA computes a variance-covariance matrix for the stored data set and extracts the eigenvalues and eigenvectors. PCA decomposes the data matrix as the sum of the outer product vector, referred to as loadings and scores. The scores contain information on how the tests or events relate to each other and the loadings contain information on how the variables or sensors relate to each other. Examination of the results of these methods provides insight into the data set. PCA analysis is used here to display the data and to select a subset of sensors (variable reduction).

Hierarchical cluster analysis, one of the exploratory algorithms, was used to investigate the natural groupings of the data based on the responses of the sensors tested in this study. Clustering techniques, which are unsupervised learning techniques because the routines are given only the data and not the classification type, group events together according to a Mahalanobis distance. By examination of the different clustering results, clear insight is gained into the actual clustering in n-space. Hierarchical cluster analysis group the data by progressively fusing them into subsets, two at a time, until the entire group of patterns is a single set. Two fusing strategies were used here, (1) k-nearest neighbor and (2) k-means. The resulting data are displayed in dendrograms and are used to determine similarities between sensor responses [10].

Classification methods are supervised learning techniques that use training sets to develop classification rules. The rules are used to predict classification of a future set of data. These methods are given both the data and the correct classification results, and they generate mathematical functions to define the classes. The best classification algorithms are those that provide the best prediction. The PNN method was used in this study because it provides a probability that the target class is present and the level of confidence can be adjusted to reduce false alarms. The PNN is a nonlinear, nonparametric pattern recognition algorithm that operates by defining a probability density function (PDF) for each data class based on the training set data and the optimized kernel width parameter. The PDF defines the boundaries for each data class. For classifying new events, the PDF is used to estimate the probability that the new pattern belongs to each data class.

PNNs are a class of neural networks that combine some of the best attributes of statistical pattern recognition methods and feed-forward neural networks [12, 13]. They have been described as the neural network implementation of kernel discriminant analysis and were first introduced into the neural network literature by Donald Specht in the late 1980's [14]. Initially developed for radar classification, the PNN has been used in a wide variety of applications

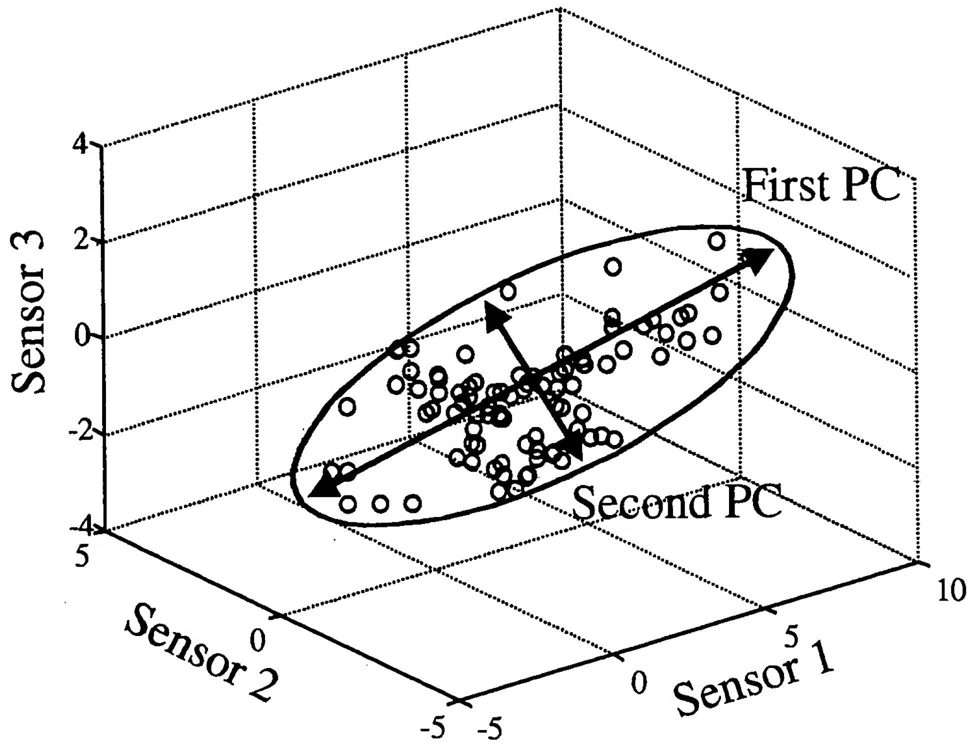


Fig. 3 – The three-dimensional representation of the Principal Component Analysis shows the values of three variables measured on a collection of samples. Principal Component 1 (First PC) describes the greatest variation in the data set, and is the major axis in the ellipse. The Principal Component 2 (Second PC) describes the direction of the second greatest variation, which is the minor axis of the ellipse.

including fingerprint identification [15], optical character recognition [15], remote sensing [16], image processing [17,18] and gas chromatography [19]. It was first used for toxic vapor identification using simulated surface acoustic wave (SAW) chemical sensor array data by Anderson [20]. This work was followed up by Shaffer and coworkers using actual SAW sensor array data from eleven different chemical warfare agents and simulants [9].

Figure 4 shows the architecture of the PNN [9]. The PNN operates by defining a probability density function (PDF) for each data class. For chemical sensor array pattern recognition, the inputs are the chemical fingerprints or pattern vectors. The outputs are the Bayesian posterior probability (i.e., a measure of confidence in the classification) that the input pattern vector is a member of one of the possible output classes.

The hidden layer of the PNN is the heart of the algorithm. During the training phase, the pattern vectors in the training set are simply copied to the hidden layer of the PNN. Unlike other types of artificial neural networks, the basic PNN only has a single adjustable parameter. This parameter, termed sigma (σ) or kernel width, along with the members of the training set define the PDF for each data class. Other types of PNNs that employ multiple kernel widths (e.g., one for each output data class or each input dimension) have become popular recently [16]. In preliminary experiments at NRL, we have not seen any large improvements in classification performance using these methods. They are not considered further in this work. In a PNN, each PDF is composed of Gaussian-shaped kernels of width σ located at each pattern vector. Cross-validation was used to determine the best kernel width. The PDF essentially determines the boundaries for classification. The kernel width is critical because it determines the amount of interpolation that occurs between adjacent pattern vectors. As the kernel width approaches zero, the PNN essentially reduces to a nearest neighbor classifier. This point is illustrated by the contour plot in Figure 5. These plots show four, two-dimensional pattern vectors for two classes (A and B). The PDF for each class is shown as the circles of decreasing intensity. The probability that a pattern vector will be classified as a member of a given output data class increases the closer it is to the center of the PDF for that class. In this example, any pattern vectors that occur inside the inner-most circle for each class would be classified with nearly 100% certainty. As σ is decreased (upper plot), the PDF for each class shrinks. For very small kernel widths, the PDF consists of groups of small circles scattered throughout the data space. A large kernel width (lower plot) has the advantage of producing a smooth PDF and good interpolation properties for predicting new pattern vectors. Small kernel widths reduce the amount of overlap between adjacent data classes. The optimized kernel width must strike a balance between a σ which is too large or too small.

Prediction of new patterns using a PNN is more complicated than the training step. Each member of the training set of pattern vectors (i.e., the patterns stored in the hidden layer of the PNN and their respective classifications), and the optimized kernel width are used during each prediction. As new pattern vectors are presented to the PNN for classification, they are serially propagated through the hidden layer by computing the dot product, d, between the new pattern

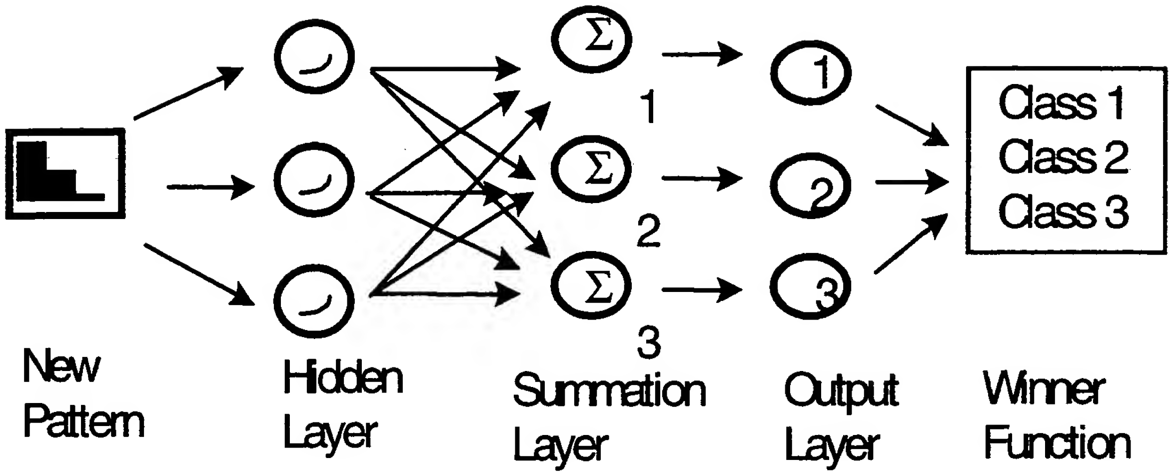


Fig. 4 – Topology of a PNN. Sensor responses are used as input and the probability of belonging to one of the specified classes is determined.

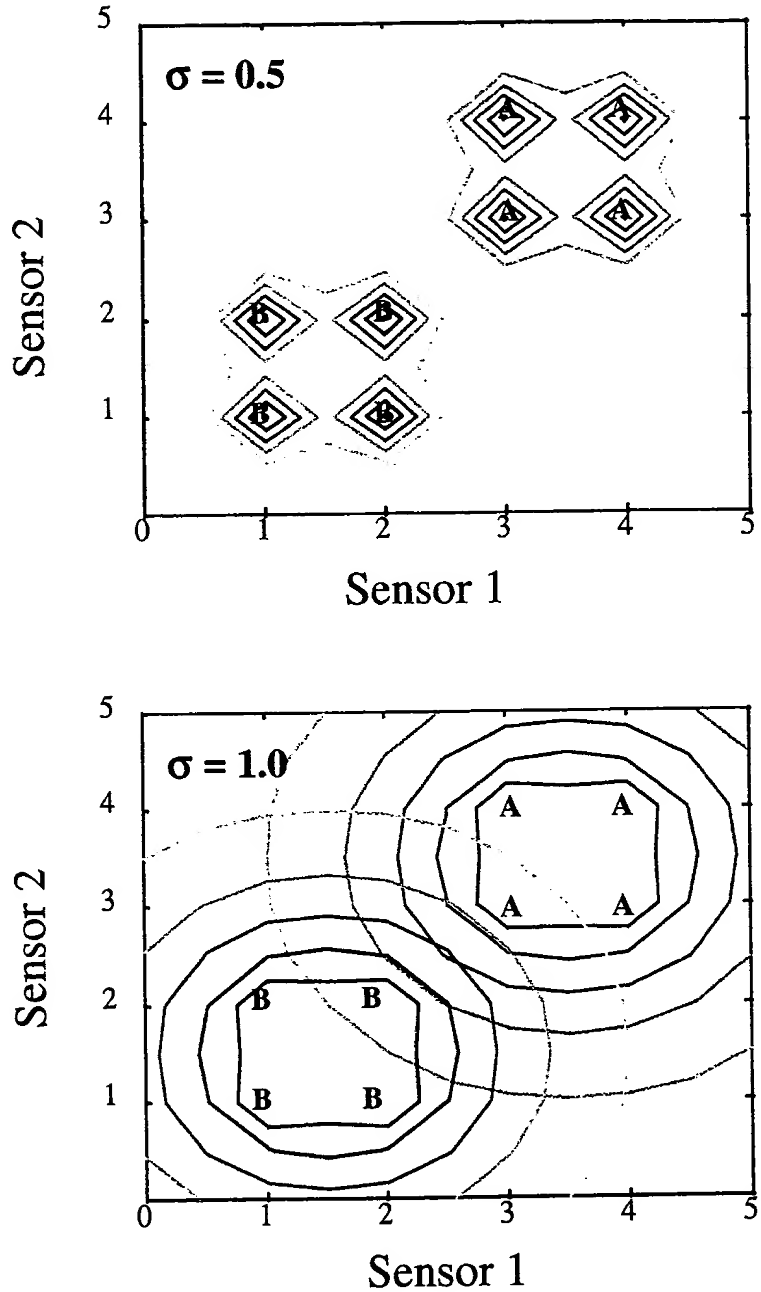


Fig. 5 – Contour plot illustrating the PDF for each class. Two classes are shown, A and B. Four events of each type are presented. The PDF for each class is shown as circles of decreasing intensity.

and each pattern stored in the hidden layer. The dot product scores are then processed through a nonlinear transfer function (the Gaussian kernel).

$$\text{Hidden\_Neuron\_Output} = \exp(-(1-d)/\sigma^2) \quad (1)$$

The summation layer consists of one neuron for each output class and simply collects the outputs from all hidden neurons of each respective class. The products of the summation layer are forwarded to the output layer where the estimated probability of the new pattern being a member of each class is computed. In the PNN, the sum of the output probabilities equals 100%.

Most of the data sets were studied using the leave-one-out cross-validation method that sequentially trains all but one observation and predicts the one that was left out. This procedure is repeated until all the observations or tests have been predicted. In addition to the leave-one-out cross-validation technique, a second approach to the analysis was also performed using the data matrix for the 0.82% alarm level. In this case, the available data was divided into a training and prediction set. Typically, at least three replicates of each source type were collected. The training set was generated by randomly selecting at least two replicates of each source type and the third replicate was put in the prediction set. For this set of experiments, the algorithm learned the training set and predicted the prediction set.

5.3.3 Part I Results

Using the data from 40 fires and 24 nuisance sources, the similarities of the sensors were examined using the correlation map. The results are shown in Figure 6. The oxygen is inversely, but highly correlated to the temperature, carbon dioxide and nitrogen dioxide sensors. The MIC sensors are highly correlated as expected, as are the two carbon monoxide sensors. The hydrogen and the temperature sensor are inversely, but highly correlated. This correlation is most likely a result of the cross-sensitivity of the H_2 electrochemical cell to temperature, more than it is a phenomenalogical result. Also as expected, the RION detector and the MIC are correlated and have a correlation coefficient of 0.7. However, the ODM sensor, the other smoke detector, was not strongly correlated to the MIC or RION sensors. This indicates that these sensors are providing unique information.

The results of the hierarchical clustering demonstrate the same trends in the data and are shown in Figure 7. The three-dimensional plot (Figure 8) generated using Principal Component Analysis (PCA) shows good separation of the different types of fires and accounts for 68% of the variance in the data set. All the fires initiate from baseline and extend into the data space and when vented, return to the baseline. Fires and nonfires are separated in space by the first principal component, while the second and third components appear to define the type of fire. The nuisance sources (in yellow) occupy a relatively distinct region in the PCA plot compared to the fire sources. These results indicate that classification methods should be very successful in identifying nonfires, fires and nuisance sources. Examination of the loadings (Figure 9) shows the relationship of the sensors. Clustering of the sensors demonstrates the high correlations

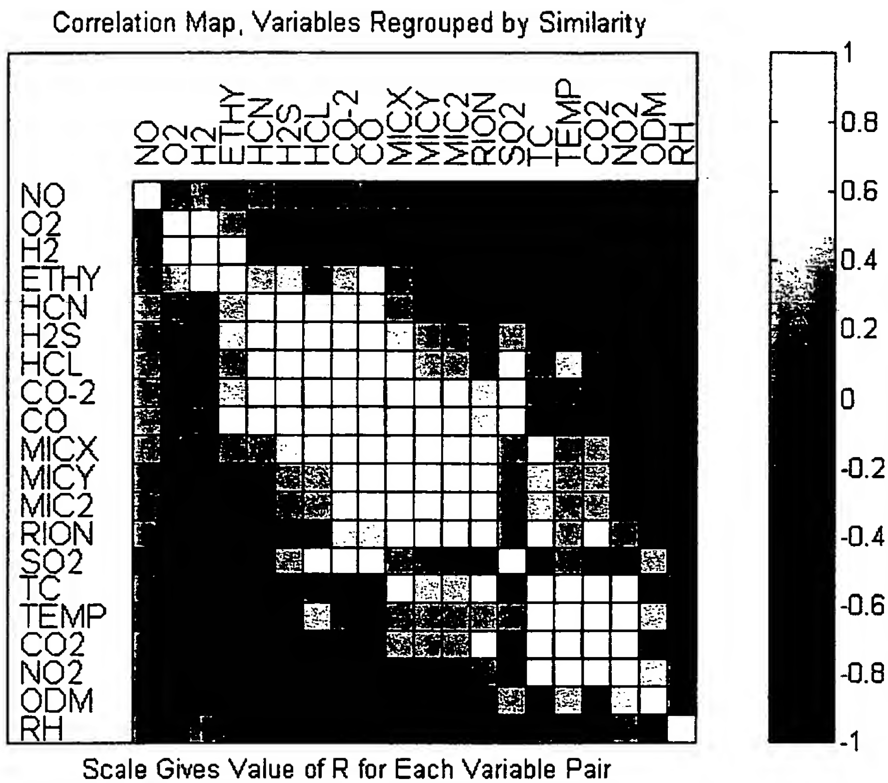


Fig. 6 – Correlation Map shows the linear independence of 20 sensor using tests for 40 fires and 24 nuisance sources. Sensors are reorganized using k-nearest neighbor. Correlated variables are near each other. Non-related variables are close to zero.

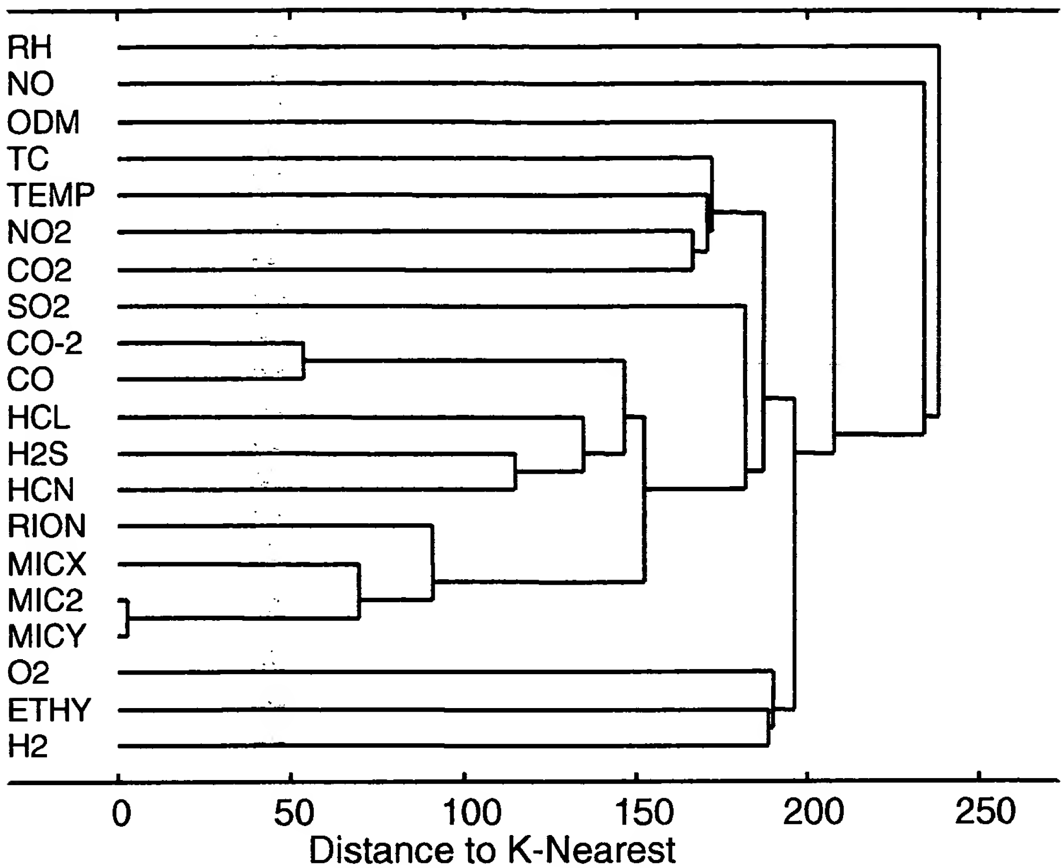


Fig. 7 – Dendrogram produced by hierarchical clustering showing the similarity of the sensors. X-Axis is a measure of increasing dissimilarity from left to right. For example, the two CO sensors produce similar response; therefore they are fused closer to the left.

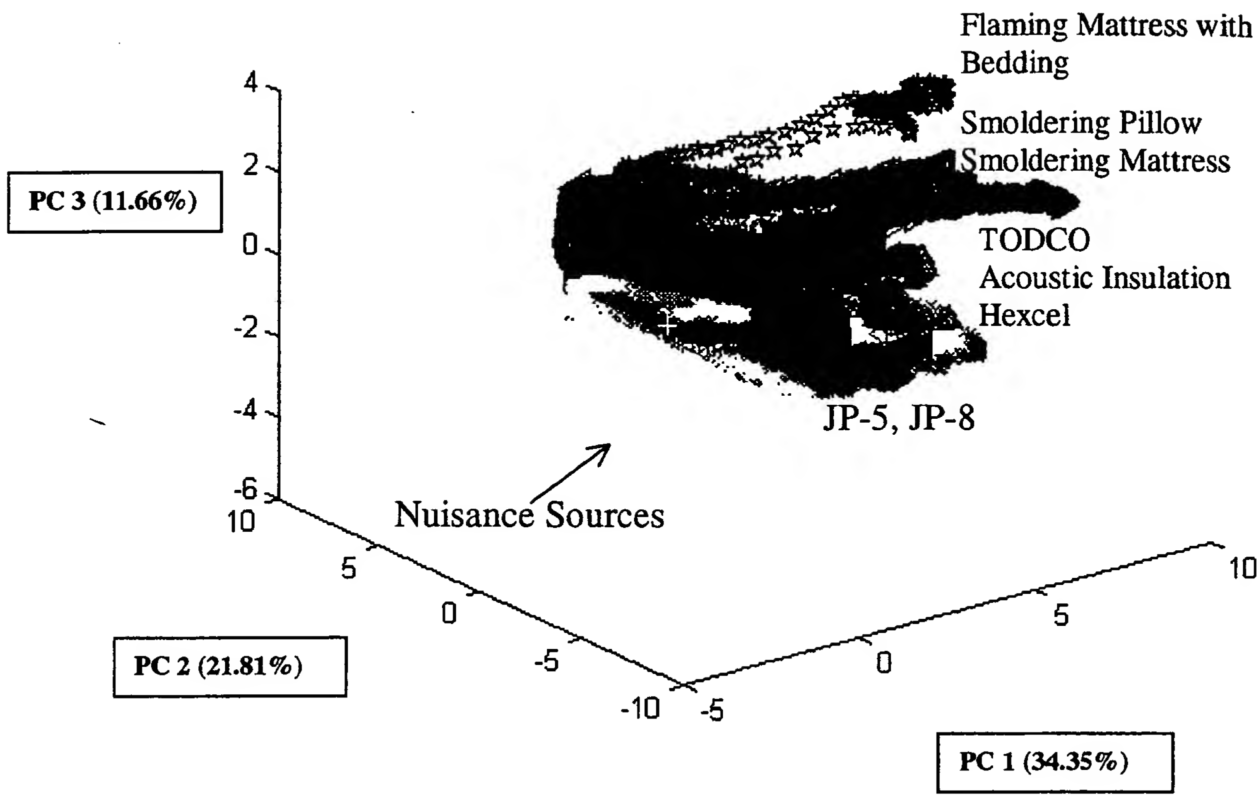


Fig. 8 – Three-dimensional PCA plot showing the responses of 20 sensors for 40 fires and 24 nuisance sources. The plot represents 68% of the variance in the data set. The fire tests initiate from the baseline or nonfire condition located at one region in the data space and project into the data space as the fire progresses. Upon termination and following chamber venting, the responses of the sensors return to the baseline. The different types of fires are well separated in the data space.

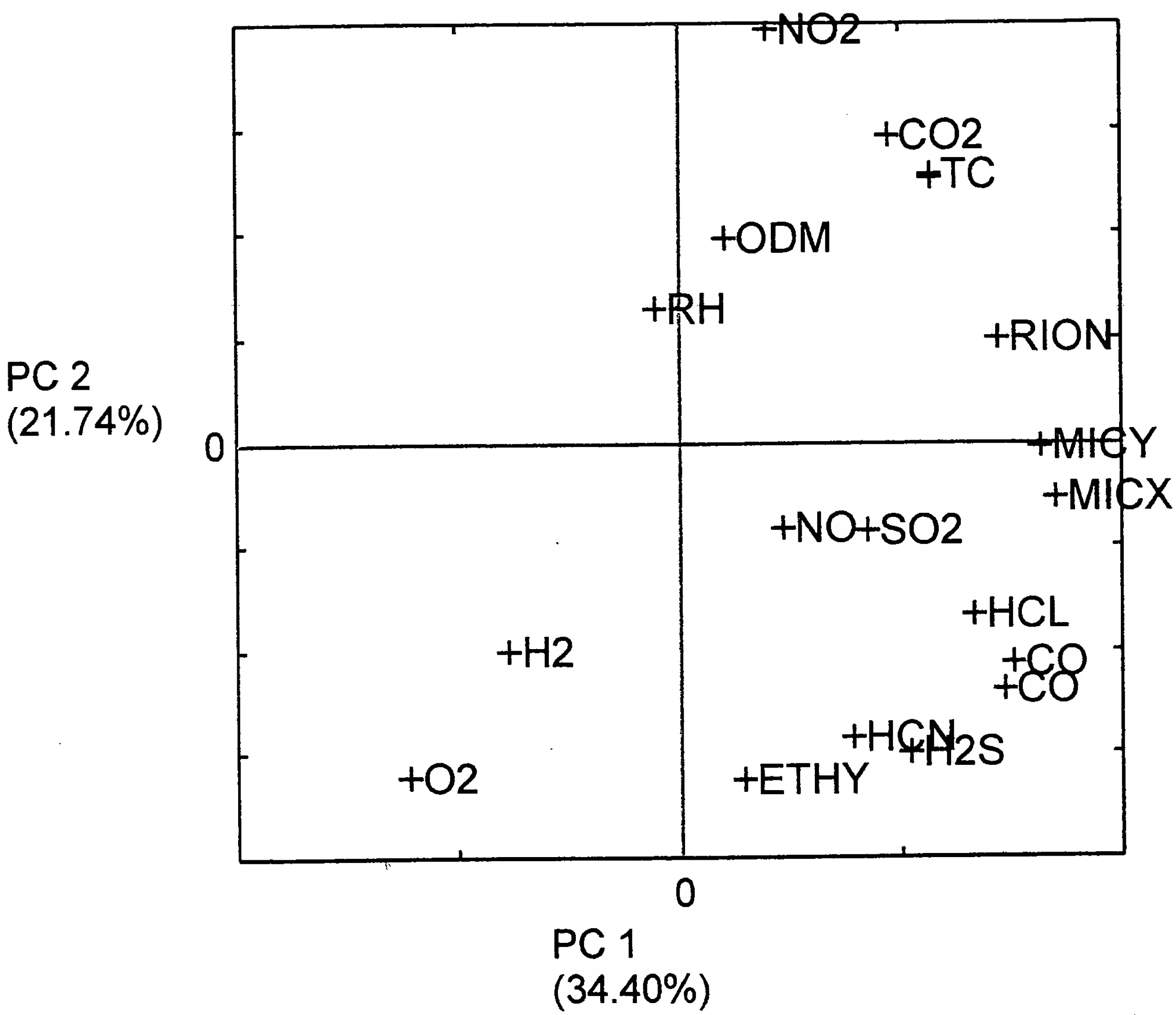


Fig. 9 – Loads plot generated by PCA shows how the sensors are related to each other. Principal component 1 (PC 1) is correlated with the separation of nonfires from fires and can be best represented by the oxygen and smoke detectors. Principal component 2 (PC 2) is correlated with the fire types and is described by a variety of sensors including ethylene, MIC, and NO_2.

revealed in the previous discussion. The oxygen sensor and the smoke detectors span the space defined by the first principal component and are, therefore, the most useful for defining a fire from a nonfire. The smoke detectors are clustered together in the space defined by the second principal component, therefore are not as useful for defining the type of event. A variety of chemical sensors can be used to span this region. For example, one set of sensors that should provide good classification consists of the following sensors: Ethylene, CO, MIC, ODM and NO_2.

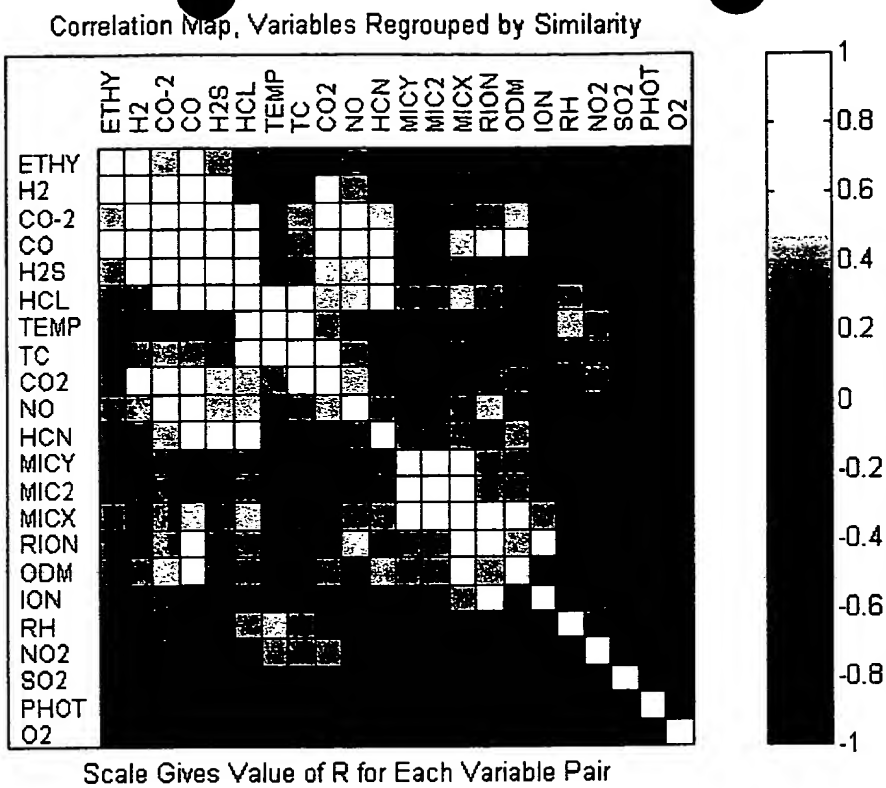
5.3.4 Part II Results

5.3.4.1 Photoelectric Alarm Level 0.82%

The correlation map and the dendrogram showing the natural clustering of the data are shown in Figure 10. Both of these methods demonstrate that the photoelectric and simplex ionization detectors are not highly correlated to the responses of the other smoke detectors. A step-wise regression technique was used to select a set of sensors that correlate to the correct classification of the data set. A chi-square test is used to determine the goodness of fit. Two sets of sensors were obtained by varying the significance level alpha. Values of 0.1, 0.05 and 0.01 were used. Using these input criteria, the best four and eight sensors were identified. The four-sensor subset identified the following sensors: MICX, RION, ODM and CO while the eight-sensor subset identified the following sensors: MICX, RION, ODM, both CO sensors, NO, CO_2 and Ethylene. Since the outputs from both of the CO sensors are highly correlated, only the $CO_{50\,ppm}$ results are discussed throughout the remainder of this report and the subscript is dropped.

The four-sensor subset, trained using the PNN, provides an overall 90% (227 of 252 events) correct classification of the data set or 25 misclassified events. Misclassifications of nonfires as nuisance sources or the reverse are not a practical concern, and were therefore not considered as misclassifications in terms of assessing performance. Misclassifications consisted of fires classified as either a nonfire or nuisance source, or a nuisance source or nonfire classified as a fire. The results for each class are shown in Table 17. There were 19 fires misclassified and 6 nuisance sources misclassified. The list of tests misclassified is given in Table 18. Most of the misclassified fires were small fires. The laundry pile fires (Tests DCAS054 and 57) should not be misclassifications. The photoelectric detector data acquisition malfunctioned for these tests and the data were erroneously set to time zero, such that all sensor values were zero. The misclassified nuisance sources were primarily due to cutting steel with a torch or grinding cinder. The burning of a single slice of toast was also misclassified. The MICX sensor malfunctioned during tests 116-121, and could have led to the misclassification of Tests 116 and 120.

a)



b)

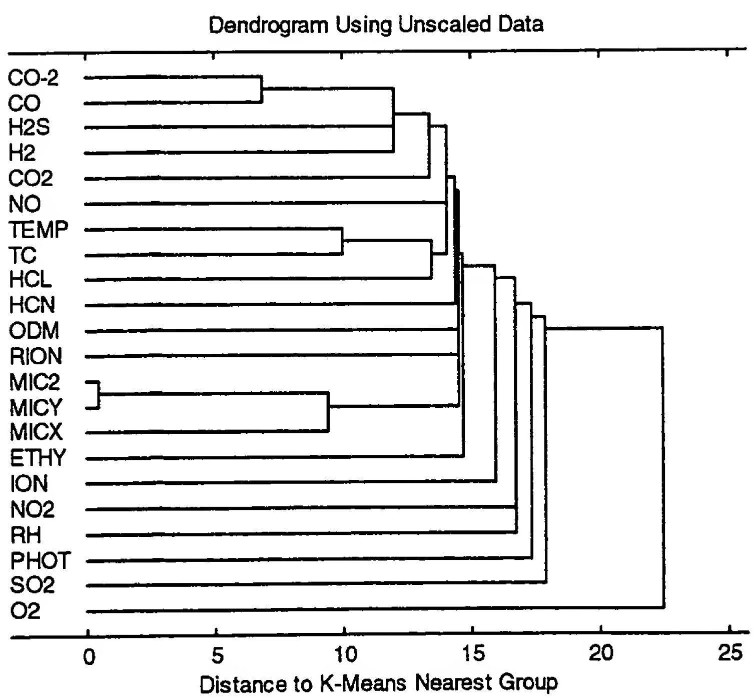


Fig. 10 – (a) Correlation matrix shows the independence of the sensors at 0.82% alarm level. Photoelectric detector is not highly correlated to the other sensors. (b) The results of hierarchical clustering show the similarity of the sensors. The simplex ionization and photoelectric detectors do not provide responses that correlate highly with other smoke detectors.

Table 17. PNN Classification Results for MICX, RION, ODM and CO at the Photo 0.82% Obs./m Alarm Level

	Number of events classified as			
Event (# of)	**Nonfires**	**Fires**	**Nuisance Sources**	**Percent Correct**
Nonfires (126)	121	0	5	100
Fires (88)	6	69	13	78
Nuisance (38)	9	6	23	84
			Overall	90

Table 18. Misclassified Events Using MICX, RION, ODM and CO at the Photo 0.82% Obs./m Alarm Level

Test ID	Scenario Type (Real/Nuisance)	Source Description
DCAS011	Real	Todco wall panel
DCAS019	Real	Todco wall panel
DCAS021	Real	Propane Meker burner
DCAS029	Real	Propane bunsen burner
DCAS030	Real	JP-5, 25 mL
DCAS035	Real	Alcohol
DCAS050	Real	Smoldering Pillow
DCAS053	Real	Heptane, 2.4 m (8 ft) from ceiling
DCAS054	Real	Laundry Pile
DCAS055	Real	Smoldering Pillow, with pillow case
DCAS057	Real	Laundry Pile
DCAS077	Nuisance	Burning Toast, one slice
DCAS083	Nuisance	Grinding cinder block
DCAS084	Nuisance	Grinding cinder block
DCAS085	Nuisance	Cutting steel with acetylene torch
DCAS087	Nuisance	Cutting steel with acetylene torch
DCAS088	Nuisance	Cutting steel with acetylene torch
DCAS101	Real	Smoldering electrical cable - LSTHOF-9
DCAS107	Real	Smoldering electrical cable - LSTPNW-1-1/2
DCAS109	Real	Flaming electrical cable - LSDSGU-50
DCAS110	Real	Flaming electrical cable - LSDGU-14
DCAS116	Real	Propane Meker burner
DCAS120	Real	Pipe insulation (NH Armaflex) fire
DCAS126	Real	Pipe insulation coated with oil (calcium silicate)
DCAS145	Real	Heptane, 2.4 m (8 ft) from ceiling

The PNN classification evaluations above were repeated four times leaving out one sensor at a time, thus producing three-sensor subsets. The results for each of these experiments are given in Table 19. The CO sensor appears to be the least important, while the ODM sensor is the most important. Even though the results suggest that the CO sensor could be dropped without a change in the overall percent correct classification, a review of the misclassifications indicate that CO is needed for correct identification of the electric heater, grinding, cigarette smoke, popcorn and gas engines. Removal of the ODM reduces the overall classification to 82% and affects the nonfire classes the most.

Table 19. PNN Classification Results for Three-Sensor Array Combinations at the Photo 0.82% Obs./m Alarm Level

	Number of Events Classified as			
	Nonfire	**Fires**	**Nuisance Sources**	**Percent Correct**
MICX, RION, ODM				
Nonfire	123	0	3	100
Fire	7	72	9	82
Nuisance Sources	7	9	22	76
			Overall	90
CO, MICX, ODM				
Nonfire	121	1	4	99
Fire	5	68	15	77
Nuisance Sources	10	13	15	66
			Overall	87
CO, MICX, RION				
Nonfire	98	8	20	94
Fire	10	63	15	72
Nuisance Sources	8	12	18	68
			Overall	82
CO, RION, ODM				
Nonfire	119	4	3	97
Fire	6	73	9	83
Nuisance Sources	11	14	13	63
			Overall	86

The photo 0.82% Obs./m database was reorganized into a training set containing two replicates (190 X 4 data matrix) of each test and a prediction set that contained the third replicate (62 X 4 matrix). The PNN classifier using the MICX, RION, ODM and CO learned the training set and predicted the prediction set with 92% accuracy (57 of 62 events). Tests DCAS021, DCAS055, DCAS098, DCAS102 and DCAS107 were misclassified (all were fire tests except Test DCAS098).

The step-wise regression method described earlier identified up to eight sensors that were correlated to the correct classification of the fires. The $CO_{4000\ ppm}$ sensor with hydrogen compensation was highly correlated to the $CO_{50\ ppm}$, so the 4000 ppm unit was not used. The three other sensors identified were nitric oxide, carbon dioxide and ethylene. Each one of these sensors was added to the original set of four to create three additional five-sensor arrays. The best results were obtained for CO NO, MIC X, ODM, RION with an overall 92% correct classification and only 19 events misclassified out of 252. Increasing the number of sensors to seven did not improve the overall results and degraded the results of the nonfire class. The 92% correct classification of the five sensor array was 2% greater than the result of the four sensor array (19 compared to 25 misclassified events).

General Atomic is currently developing novel sensors for the DC-ARM program. Currently, they are focused on devices that can detect CO_2, O_2, CO and temperature. Other sensors, such as hydrocarbons and NO could be developed using the same technology. Several four-sensor combinations were generated and tested using these sensor types. The results are given in Table 20. The overall classification decreased to 81%, however, the nuisance source classifications improved to about 90%. It appears that CO_2, O_2 and CO give the best results for nuisance sources, while the smoke detectors are best for fires.

5.3.4.2 Photoelectric Alarm Level 1.63%

The correlation map and dendrogram for this alarm level did not significantly differ from those from the 0.82% Obs./m data set. Variable selection resulted in the same set of sensors as identified for the lower alarm level. The PNN classifier was used to train the four-sensor array consisting of MICX, RION, ODM and CO. The results, shown in Table 21a, reveal 92% overall classification accuracy and 19 missed events. The biggest improvement is seen for the nuisance sources. The list of misclassified events is given in Table 22. Addition of the NO sensor does not improve the overall classification, but including all eight sensors does improve the results to 94% with 15 events misclassified as shown in Table 21b.

The PNN classification evaluations were repeated four times leaving out one sensor at a time, thus testing three-sensor arrays (Table 23). Removal of CO, or MICX produced similar overall classification results with about 90% of the events correctly identified, while removal of the ODM or RION sensors degraded the overall classification significantly and had greatest impact on both the fire and nuisance classes.

Table 20. PNN Classification Results for Various Sensor Combinations at the Photo 0.82% Alarm Level

Sensor Set	Number Wrong	Percent classified correctly: Nonfire	Fire	Nuisance	Overall Percent Correct
CO_2, O_2, CO, ethylene	49	90	61	92	81
CO_2, O_2, CO, Temp (TC)	49	90	64	87	81
CO_2, O_2, CO, NO	43	97	61	87	83

Table 21. PNN Classification Results for (a) a Four Sensor and (b) a Eight Sensor Combination at the Photo 1.63% Obs./m Alarm Level

(a) MICX, RION, ODM and CO

	Number of events classified as: Nonfires	Fires	Nuisance Sources	Percent Correct
Nonfires	120	0	6	100
Fires	5	72	11	82
Nuisance Sources	5	3	30	92
			Overall	92

(b) MICX, RION, ODM, $CO_{50\ ppm}$, $CO_{4000\ ppm}$, NO, CO_2 and Ethylene

Event	Number of events classified as: Nonfires	Fires	Nuisance Sources	Percent Correct
Nonfires	120	1	5	99
Fires	4	77	7	88
Nuisance Sources	6	3	29	92
			Overall	94

Table 22. Misclassified Events Using MICX, RION, ODM and CO at the Photo 1.63% Alarm Level

Test ID	Scenario Type (Real/Nuisance)	Source Description
DCAS011	Real	Nomex, honeycomb wall panel
DCAS012	Real	Heptane, 1.2 m from ceiling
DCAS019	Real	TODCO wallboard
DCAS029	Real	Propane bunsen Burner
DCAS030	Real	JP-5
DCAS035	Real	Alcohol
DCAS036	Real	Alcohol
DCAS053	Real	Heptane, 2.4 m (8 ft) from ceiling
DCAS054	Real	Laundry Pile
DCAS055	Real	Smoldering Pillow
DCAS057	Real	Laundry Pile
DCAS087	Nuisance	Cutting steel with acetylene torch
DCAS088	Nuisance	Cutting steel with acetylene torch
DCAS102	Real	Smoldering Electrical cable LSTHOF-9
DCAS107	Real	Smoldering Electrical cable LSTPNW-1-1/2
DCAS109	Real	Flaming electrical cable - LSDSGU-50
DCAS116	Real	Propane Meker burner
DCAS120	Real	Pipe insulation (NH Armaflex) fire

Table 23. Three-Sensor Array Combinations and Results at the Photo 1.63% Alarm Level

MICX. RION. ODM	Nonfire	Fires	Nuisance Sources	Percent Correct
Nonfire	125	0	1	100
Fire	5	72	11	82
Nuisance Sources	3	8	27	80
			Overall	80
CO, MICX, ODM				
Nonfire	122	0	4	100
Fire	5	70	13	80
Nuisance Sources	4	10	24	74
			Overall	89
CO, MICX, RION				
Nonfire	125	0	1	100
Fire	7	66	15	77
Nuisance Sources	5	9	24	76
			Overall	88
CO, RION, ODM				
Nonfire	123	0	3	100
Fire	4	71	13	81
Nuisance Sources	8	6	24	84
			Overall	91

The combinations that may be developed by General Atomic were also investigated. The results were much improved over the 0.82% alarm level, although still not as good as the set of four shown above. Table 24 shows the results.

Table 24. PNN Classification Results for Various Sensor Combinations at the Photo 1.63% Alarm Level

		Percent Classified Correctly			
Sensor Set	Number Wrong	Nonfire	Fire	Nuisance	Overall Percent Correct
CO_2, O_2, CO, Ethylene	27	93	73	89	85
CO_2, O_2, CO, Temp (TC)	33	96	73	89	87
CO_2, O_2, CO, NO	29	97	78	84	83

5.3.4.3 Photoelectric Alarm Level 11%

The correlation map and dendrogram for this alarm level reveal a higher correlation between the smoke detectors as shown in Figure 11. In particular, the simplex ionization sensor is correlated to the RION and MICX sensors by 60-70% and the photoelectric sensor is correlated to ODM and MICX sensors by 40%. Variable selection resulted in the same set of eight sensors as identified above although the order of the sensors varied. The original set of four sensors and the new set were both investigated. The PNN classifier was used to train the four-sensor array identified at the lower alarm levels, consisting of MICX, RION, ODM and CO. The results, shown in Table 25a, reveal 94% overall classification accuracy and 16 missed events. The biggest improvement is seen for the real fires. The list of misclassified events is given in Table 26.

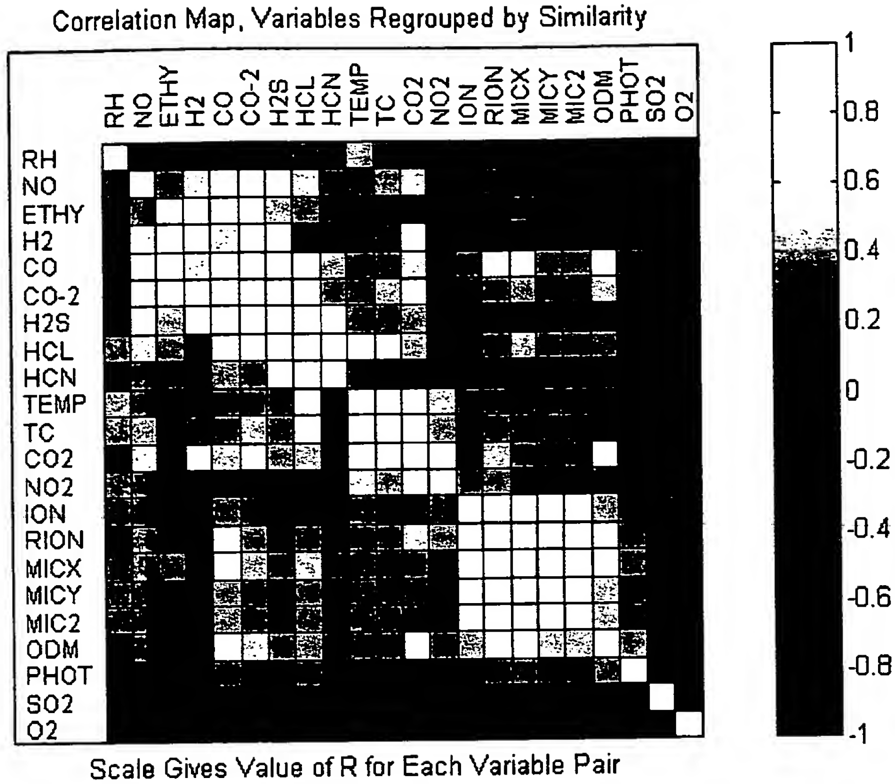
A second set of four sensors was also tested representing the top four sensors in the list produced by the variable selection method. The new four-sensor subset consisted of MICX, RION, CO and Ethylene. The overall classification results degraded to 90% with 26 misclassified events as shown in Table 25b. Another four-sensor subset, CO, ODM, ION and PHOT, was generated by substituting the photoelectric and simplex ionization sensors for the RION and MICX sensors in the original set of four. The overall classification results were 94%, the same as the original four-sensor subset. The PNN classifier was also used to train the eight-sensor subset. The overall classification is improved to 95% with only 12 events missed.

Table 25. PNN Classification Results for (a) the Original Four Sensors and (b) the Top Four Sensors at the Photo 11% Obs./m Alarm Level

(a) MICX, RION, ODM and CO				
	Number of events classified as			
	Nonfires	**Fires**	**Nuisance Sources**	**Percent Correct**
Nonfires	120	1	5	99
Fires	5	77	6	88
Nuisance Sources	6	4	28	89
			Overall	94

(b) MICX, RION, CO and Ethylene				
	Number of events classified as			
Event	**Nonfires**	**Fires**	**Nuisance Sources**	**Percent Correct**
Nonfires	124	1	1	99
Fires	12	69	7	78
Nuisance Sources	17	6	15	84
			Overall	90

a)



b)

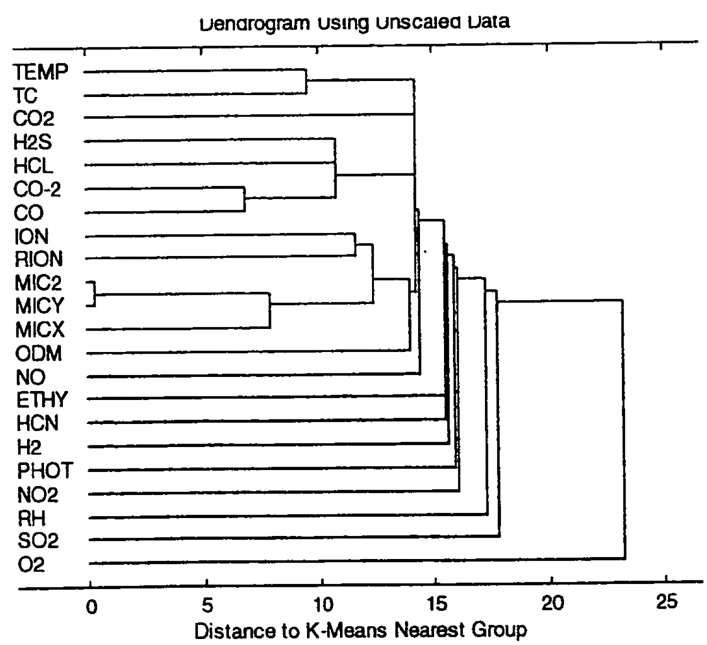


Fig. 11 – (a) Correlation matrix shows the independence of the sensors at the 11% alarm level. (b) The results of hierarchical clustering show the similarity of the sensors. The Simplex ionization and photoelectric detector responses are more highly correlated with the responses of the other smoke detectors than at previous alarm levels.

Table 26. Misclassified Events Using MICX, RION, ODM, at the CO at the Photo 11% Alarm Level

Test ID	Scenario Type(Real/Nuisance)	Source Description
DCAS015	Real	Smoldering Mattress with bedspread, blanket and 2 sheets
DCAS024	Real	Heptane, 1.2 m from
DCAS029	Real	Propane bunsen Burner
DCAS035	Real	Alcohol (70%)
DCAS041	Real	Heptane, 1.2 m from
DCAS054	Real	Laundry Pile
DCAS055	Real	Smoldering Pillow
DCAS057	Real	Laundry Pile
DCAS075	Nuisance	Burning Toast, one slice
DCAS085	Nuisance	Cutting steel with acetylene torch
DCAS087	Nuisance	Cutting steel with acetylene torch
DCAS088	Nuisance	Cutting steel with acetylene torch
DCAS116	Real	Propane Meker burner
DCAS120	Real	Pipe Insulation (NH Armaflex) fire
DCAS123	Real	Pipe Insulation coated with oil fire (NH Armaflex)
DCAS125	Real	Pipe Insulation coated with oil fire (calcium silicate)

The PNN classification evaluations were repeated four times leaving out one sensor at a time, thus testing three-sensor arrays (Table 27). Removal of the CO, RION or MICX sensor produced similar overall classification results of 90%, while removal of the ODM sensor degraded the overall classification to 86% and has a big impact on the ability to classify real fires.

Table 27. Three-Sensor Array Combinations and Results at the Photo 11% Alarm Level

MICX, RION, ODM	Nonfire	Fires	Nuisance Sources	Percent Correct
Nonfire	123	0	3	100
Fire	5	68	15	77
Nuisance Sources	5	4	29	89
			Overall	89
CO, MICX, ODM				
Nonfire	126	0	0	100
Fire	7	69	12	78
Nuisance Sources	10	4	24	89
			Overall	91
CO, MICX, RION				
Nonfire	126	0	0	100
Fire	19	57	12	65
Nuisance Sources	19	5	14	87
			Overall	86
CO, RION, ODM				
Nonfire	123	0	3	100
Fire	4	70	14	80
Nuisance Sources	8	8	22	79
			Overall	90

The combinations that may be developed by General Atomic were also investigated. The results for these sets have improved with each alarm level, although they are still not as good as the four identified by variable selection. Table 28 presents the results. The weakest class performance is observed in the real fire class. Previous tests have shown the importance of smoke detectors in classifying fires. Therefore, two additional subsets of sensors were investigated including the ODM and MICX sensors. Table 29a shows the results for CO_2, O_2, CO and ODM. This set has an overall classification of 92% and is an improvement over the results shown in Table 28. When the MICX sensor is also added (Table 29b), the overall classification results of 94% are the same as those produced with the CO and smoke detectors.

Table 28. Classification Results for Various Sensor Combinations at the Photo 11% Alarm Level

Sensor Set	Number Wrong	Percent Class 1 Correct	Percent Class 2 Correct	Percent Class 3 Correct	Overall Percent Correct
CO_2, O_2, CO, ethylene	25	97	78	95	90
CO_2, O_2, CO, temperature	29	94	82	87	88
CO_2, O_2, CO, NO	22	98	73	87	91

Table 29. PNN Classification Results for Alternate Chemical Sensor Combinations at the Photo 11% Alarm Level

(a) CO_2, O_2, CO and ODM				
	Number of events classified as			
	Nonfires	**Fires**	**Nuisance Sources**	**Percent Correct**
Nonfires	126	0	0	100
Fires	5	71	12	81
Nuisance Sources	4	4	30	89
			Overall	92

(b) CO_2, O_2, CO, ODM and MICX				
	Number of events classified as			
Event	**Nonfires**	**Fires**	**Nuisance Sources**	**Percent Correct**
Nonfires	124	1	1	99
Fires	5	77	6	88
Nuisance Sources	3	4	31	89
			Overall	94

5.3.5 Discussion

This section demonstrates the usefulness of multivariate methods for understanding large fire/nuisance source databases. In particular, the methods have been used to select the optimal set of sensors to achieve the best classification results for a large number of real fires and nuisance sources.

In Part I, the cluster and display methods all reveal similar information about how the sensors are related to each other. The analysis shows a high correlation between the two CO sensors. Therefore, either sensor would provide the same information. The residential ionization

detector (RION) was also highly correlated (>80%) to the Measuring Ionization Chamber (MIC), and the oxygen sensor was highly, but inversely, correlated to the temperature and CO_2 sensors. Otherwise the correlation between the sensors was minimal. Using these techniques, a subset of ten sensors could be selected to explain much of the information contained in all 20 sensors.

The principle component analysis (PCA) plot in Part I, representing the entire event test from initiation to termination (i.e., all transient data for each test), shows good separation of the event tests by type. Replicates and similar sources such as JP-5 and JP-8 cluster near each other. These results indicate that excellent discrimination of fires should be possible with the sensors tested here. The PCA loadings reveal which sensors contribute to separation in the data space and, therefore, would be most useful for classification. Principal component 1 (PC 1) describes the progression of the fire/nuisance sources from baseline until termination and compartment venting. The oxygen sensor (or temperature and CO_2 sensors since they are highly, but inversely correlated to the oxygen sensor) and the residential ion (RION), CO and MIC sensors span the space defined by the PC 1. Therefore the oxygen and one of the smoke detectors would be most useful in defining the temporal nature of the fire and would likely do well for discriminating nonfires from fire/nuisance sources. Principal component 2 (PC 2) defines the type of fire. In addition, this component is more like a discrete moment in time and should relate more closely to the analyses conducted in Part II of the multivariate study. The following set of eight sensors span the data space defined by the PC 2: NO_2, CO_2, ODM, RION, MICX, NO, CO, Ethylene. Even though the classification analysis in Part II only addressed discrete time data sets, most of the above sensors were selected in the Part II analysis using variable selection and demonstrated very good classification results. The NO_2 sensor was the only sensor not identified in Part II and, therefore, not included in the Part II PNN evaluations. There are several explanations for this observation. The NO_2 sensor performance degraded over the course of the event tests, therefore the variance in the sensor may not have correlated highly with the classification of the events. It is also possible that the NO_2 responses do not contribute to the three categories (nonfire, fire and nuisance sources) defined in Part II, or alternatively, the responses may become more important in a temporal analysis.

Part II of the multivariate study investigated the ability of small subsets of sensors to classify the fire and nuisance source tests into three categories: nonfire, fire and nuisance sources. If a nonfire or nuisance source was identified as a fire or if a fire was identified as either a nonfire or nuisance source, this was considered a misclassification. These studies not only provided information about which sets of sensors produce the most accurate classifications, inspection of the missed classes and fires reveal what types of information are being encoded by the sensors. Three different photoelectric alarm levels were used and the classification results improved as the event progressed (i.e., at greater alarm levels). Inspection of the most often misclassified tests reveals that they were very small fires or particularly difficult nuisance sources. At the earliest photoelectric alarm level (0.82% Obs./m), 90% correct classification of the data (25 missed) is achieved with only four sensors, CO, MICX, RION and ODM. As expected, the classification results improve as the events progress as indicated by the three alarm levels. At 11% obscuration

per meter, 94% correct classification (16 missed) was achieved with the same set of four sensors. Most of the improvement is seen in the nuisance source class.

Three-sensor subsets were investigated by leaving out one sensor at a time from the above set. In all the cases and for each alarm level the number of correct classifications decreases. When the ODM sensor is removed, the performance degrades the most therefore indicating the importance of that sensor. As discussed previously, the MIC is not a practical sensor that can be incorporated into a detector as it exists. Rather it is a standardized ionization chamber used for evaluating ionization detectors. Therefore, it was expected that the MIC would correlate highly to both the Simplex ionization detector and the residential ionization detector (RION). Though a correlation existed (<80%), it was not so high that the sensors provided purely redundant information. Consequently, the top four sensors identified as providing good discrimination included both the RION and the MIC (note, the Simplex ionization detector was not in the top eight sensors and was not highly correlated to the other smoke sensors). The results of the three ionization type sensors indicate that the design of the ionization sensor may also be as important to developing an effective multi-signature detector as is the inclusion of an ionization sensor. In light of the practical considerations, the MIC was excluded from the sensor array and the performance of this three sensor subset was evaluated. The overall percent classification results obtained without the MIC (i.e., for the CO, RION and ODM) were 87% at the 0.82% alarm level, 91% at the 1.63% alarm level and 90% at the 11% alarm level. This overall performance compares well to the conventional smoke detectors, which had corresponding overall classification results of 83, 83 and 76% for the photoelectric detector and 88, 88 and 85% for the ionization detector. The data shows that the overall performance of the detectors and the multi-signature algorithms decreases as the alarm threshold increases from 1.63 to 11%. This is due to a reduction in the number of fires correctly classified at the highest alarm level. As discussed previously (Sec. 4.6), due to the incipient nature of the fire sources, some fires were too small for the smoke detectors to detect at the highest alarm level. The results presented show that the multi-signature algorithms are capable of detecting more fires than the smoke detectors, given the same set of data (i.e., the 11% alarm signature database) for incipient fires.

Several other sensor subsets excluding the MIC were investigated as potential combinations for providing greater improvements compared to conventional smoke detectors. As discussed earlier, at the 0.82% alarm level, a five-sensor set consisting of CO, MICX, RION, ODM and NO provided the best results with an overall classification of 92% and 19 missed events. When MICX is removed from this set (see Table 30), the results are reduced to 89% and 28 missed events. At the 1.63% and 11% alarm levels, this set of sensors produced 92% and 91% correct classification, respectively. These results are slightly better than the results produced by the three-sensor subset CO, RION and ODM, but are still not as good as the top four sensor suite CO, MICX, RION and ODM which had overall classification results of 90, 92 and 94%, respectively. However, considering the MIC issue, CO, NO, RION and ODM may be a more practical sensor array for field applications because it yields improved results over conventional smoke detectors.

Table 30. PNN Classification Results for CO, NO, ODM and RION at (a) 0.82%, (b) 1.63% and (c) 11%

(a)0.82%

	Number of events classified as			
Event	**Nonfires**	**Fires**	**Nuisance Sources**	**Percent Correct**
Nonfires	120	1	5	99
Fires	4	71	13	81
Nuisance Sources	10	9	19	76
			Overall	89

(b)1.63%

	Number of events classified as			
Event	**Nonfires**	**Fires**	**Nuisance Sources**	**Percent Correct**
Nonfires	121	0	5	100
Fires	7	73	11	83
Nuisance Sources	7	6	25	84
			Overall	92

(c) 11%

	Number of events classified as			
Event	**Nonfires**	**Fires**	**Nuisance Sources**	**Percent Correct**
Nonfires	121	1	4	99
Fires	4	73	11	83
Nuisance Sources	8	7	23	82
			Overall	91

Several combinations of only gas and temperature sensors were also investigated due to their relevance to the work being conducted at General Atomic. While the overall classification results for various combinations of CO_2, O_2, CO, Ethylene, Temperature and NO were much worse than the four-sensor subsets above, the identification of nuisance sources improved 25% for the lowest alarm level. This suggests these sensors may be useful for early detection and discrimination. In the tests described above and in others conducted during this study, smoke detectors are shown to be important for discriminating fires and the ODM sensor demonstrated the best performance. Considering these observations, a subset was tested using CO_2, O_2, CO, ODM and RION at each of the alarm levels as shown in Table 31. At the 0.82% alarm level, only 22 tests were misclassified providing 91% correct classification. Little improvement is seen above this alarm level indicating the responses have reached a plateau. These results suggest that earlier detection is possible with this set of sensors. Therefore, this set is a good combination of chemical vapor sensors and smoke detectors providing much improvement over the standard smoke detector particularly with regard to recognition of nuisance sources.

Table 31. PNN Classification Results for CO_2, O_2, CO, RION and ODM at (a) 0.82%, (b) 1.63% and (c) 11%

(a)0.82%

	Number of events classified as			
Event	**Nonfires**	**Fires**	**Nuisance Sources**	**Percent Correct**
Nonfires	123	1	2	99
Fires	7	71	10	81
Nuisance Sources	7	4	27	89
			Overall	91

(b)1.63%

	Number of events classified as			
Event	**Nonfires**	**Fires**	**Nuisance Sources**	**Percent Correct**
Nonfires	125	1	0	99
Fires	5	73	10	83
Nuisance Sources	2	5	31	87
			Overall	92

(c) 11%

	Number of events classified as			
Event	**Nonfires**	**Fires**	**Nuisance Sources**	**Percent Correct**
Nonfires	126	0	0	100
Fires	5	72	11	82
Nuisance Sources	2	5	31	87
			Overall	92

Standard smoke detectors can provide either early fire detection with a high false alarm rate or low fire detection rates. Multi-criteria sensors or sensor arrays allow the user to select sensors for both early fire detection and high rejection of nuisance sources. For most of the sensor combinations tested in this report, the most significant improvement is observed for discrimination of nuisance sources. Selection of the appropriate sensor sets can be guided by multivariate analysis, but the final decision must include practical assessments such as the availability of sensors, reliability and long-term stability. Based on the results of this study, the following sets are recommended for consideration.

CO, NO, RION and ODM
CO_2, O_2, CO, ODM and RION
CO, MICX, RION and ODM

Tables 32-34 summarize the performance of the candidate sensor combinations when used with the PNN. The results of the candidate sensor sets are compared to the performance results of the commercial photoelectric and ionization smoke detectors (Simplex units). Table 32 presents the overall percent correct classification achieved at the three photoelectric alarm level data sets (0.82, 1.63 and 11% Obs./m). The percent classification values are the same results presented earlier for each sensor combination and for the smoke detectors (see Table 11). The results for the ionization smoke detector are reported for alarms occurring at 0.82, 1.63 and 4.2% Obs./m, respectively. These alarm thresholds represent the corresponding alarm levels for half the UL minimum, the UL minimum and typical alarm levels as noted for the photoelectric detector. The results in Table 32 show improved performance for all of the candidate sensor combinations at every alarm level compared to both of the smoke detectors. The best improvement in performance is from the combination CO, MICX, RION and ODM. Compared to the photoelectric detector, the multi-sensor combination correctly classified 46 more events at the 11% Obs./m level. The results show that the multi-signature detection algorithms are more sensitive to detecting real fires while also improving nuisance alarm immunity.

The performance improvements are presented in more detail in Tables 33 and 34. Table 33 shows the number of real fire events correctly classified by the candidate sensor combinations compared to the commercial smoke detectors. Table 34 shows the number of false alarms incurred by each of the sensor combinations and the smoke detectors. The number of false alarms equals the number of nuisance or nonfire sources classified as fire. As can be seen in Table 33, the smoke detectors are able to detect more fire events as the alarm threshold is reduced. The multi-signature alarm algorithms are able to maintain nearly the same performance at each alarm level data set. In addition, the multi-signature alarm algorithms were generally able to identify more fire events than the smoke detectors. The improvement is particularly noticeable at the typical alarm threshold level (bottom row of table), where the photoelectric detector alarmed for 34 fires and the ionization detector alarmed for 62 fires compared to 77 to 72 fires by the three multi-signature alarm algorithms. The results clearly show that the conventional smoke detectors signaled significantly fewer fire alarms for the small incipient fires when set at typical alarm thresholds (e.g., 11% for photoelectric).

As noted, improved detection performance with the smoke detectors can be achieved by lowering the alarm threshold. However as shown in Table 34, the number of nuisance alarms increases. For example, by reducing the alarm level from 11 to 0.82% Obs./m, the photoelectric detector experiences 7 to 18 nuisance alarms, respectively. The candidate multi-signature alarm algorithms are able to maintain approximately the same nuisance alarm rate at all of the alarm levels. More importantly, the multi-signature alarm algorithms yield significantly fewer nuisance alarms than the smoke detectors. Overall, the results show that the three candidate sensor combinations used with a PNN are able to provide increased detection sensitivity and improved nuisance alarm immunity.

Table 32. Overall Percent Correct Classification[1] for Three Candidate Sensor Combinations Using a PNN Compared to the Commercial Smoke Detectors

Photo % Obs./m Alarm Level Data Set	Photoelectric	Ionization[2]	CO, MICX, RION, ODM	CO, NO, RION, ODM	CO_2, O_2, CO, RION, ODM
0.82	83	88	90	89	91
1.63	83	88	92	92	92
11	76	85	94	91	92

[1] One percentage point equals 2.5 events.
[2] The ionization detector data represents alarms at 0.82, 1.63 and 4.2% Obs./m, respectively.

Table 33. Number of Real Fire Sources Correctly Classified by the Candidate Sensor Combinations Compared to the Commercial Smoke Detectors

Photo % Obs./m Alarm Level Data Set	Photoelectric	Ionization[1]	CO, MICX, RION, ODM	CO, NO, RION, ODM	CO_2, O_2, CO, RION, ODM
0.82	64	75	69	71	71
1.63	62	72	72	73	73
11	34	62	77	73	72

[1] The ionization detector data represents alarms at 0.82, 1.63 and 4.2% Obs./m, respectively.

Table 34. Number of False Alarms (nuisance or nonfire sources classified as fires) by the Candidate Sensor Combinations Compared to the Commercial Smoke Detectors

Photo % Obs./m Alarm Level Data Set	Photoelectric	Ionization[1]	CO, MICX, RION, ODM	CO, NO, RION, ODM	CO_2, O_2, CO, RION, ODM
0.82	18	16	6	9	4
1.63	18	15	3	6	5
11	7	11	4	7	5

[1] The ionization detector data represents alarms at 0.82, 1.63 and 4.2% Obs./m, respectively.

6.0 LIMITATIONS AND ASSUMPTIONS

This section discusses key limitations and assumptions of the work performed in this study.

(1) Although good experimental design was used in developing this database, it is realized that there are potential limitations. It may be necessary to expand the number of nuisance source classifications and background events to develop a robust alarm algorithm.

(2) The work done to date has consisted primarily of discrete analyses. As the results of these analyses indicate, the use of transient signature patterns may yield improved fire detection and discrimination performance.

(3) The database of signature patterns is based on single sensor measurements for most signatures except smoke level. The decrease in performance of several gas sensors (e.g., SO_2, NO_2 and Ethylene) over the course of the test series can lead to biases in the data analyses. The exclusion of these sensors from candidate combinations for fire detection systems (based on the multivariate analyses) may indicate that these signatures were not important or may be a result of biases. A review of the results and the chemistry of the real fire and nuisance sources indicates that these signatures would not be prime candidates, and therefore any potential bias may not be an issue.

The results indicate that the instrumentation design, as well as the principle of operation, used for smoke measurements is important. Therefore, a more detailed understanding of the technologies and characterization of particulates from sources is needed to develop an optimized, practical fire detector. The use of only one brand of commercial smoke detectors limits the comparison of multi-signature alarm algorithm performance to that brand. Other brand detectors may or may not perform better than the Simplex detectors used in this study; sufficient data are not available to fully assess performance of other detector models to fires and nuisance alarm sources.

(4) Algorithms developed on the database obtained in this program will need to be optimized with the final sensor array chosen for prototype development. This will be necessary due to the fact that sensors will have varying characteristics, such as sensitivity, selectivity, response time and reliability compared to those utilized in this work.

(5) The univariate analysis performed in this study used sensor measurements reported as changes above ambient conditions. The data were converted to changes from ambient by subtracting the average ambient value from each data point. The ambient value for each of the sensors was calculated as the average value for the 60 seconds prior to source initiation.

The commercial ionization and photoelectric smoke detection system uses processing technology that accounts for the ambient smoke level in calculating the alarm condition. In other words, the smoke detectors measure the change in smoke level compared to the ambient condition. This processing technique is commonly used to enable addressable systems to assess and account for detector fouling as well as changes in the environment which are not associated with a fire event. For example, in a warehouse environment, certain activities may cause dust levels to gradually increase during normal operations and cause detectors to read elevated levels of "smoke." A detector which has a fixed smoke level alarm criteria would consequently become more sensitive to fires or other nuisance alarm events. If a detection system is able to account for gradual changes in background "smoke" levels, the sensitivity of the system can be maintained.

The concept of accounting for changing ambient conditions is, potentially, very important with a multi-sensor detector measuring signatures that routinely change over time or vary according to geographical location. For example, using an absolute value of temperature for an alarm threshold can lead to nuisance alarms if the threshold is not greater than extreme ambient temperatures. An early warning detection system may need to detect a fire with overhead gas temperatures of 38°C (100°F); however, this value will certainly be exceeded in certain regions of the world based solely on weather conditions. A more useful alarm threshold would be to detect a change above ambient, such as 11°C (20°F). The multivariate analyses used the actual processed data which was not adjusted for ambient conditions (see Sec. 5.1).

Ultimately, variations in ambient conditions will need to be more fully addressed by the multivariate algorithms. It is likely that the database will need to be expanded to include more detailed background fluctuations before these methods can be fully implemented.

7.0 SUMMARY AND CONCLUSIONS

This report presented the findings of an experimental program aimed at developing a multi-signature early warning fire detection system for Navy shipboard applications. The detection system is to provide reliable warning of actual fire conditions in less time with fewer nuisance alarms than can be achieved with commercially available smoke detection systems. This report documented the experimental testing conducted to develop a database of signatures from fire and nuisance source events. One hundred and twenty six tests were included in the database, representing 26 different fire scenarios and 12 nuisance sources.

Signature databases of 22 sensor outputs were used as the basis for univariate and multivariate data analyses. The univariate analysis evaluated individual sensor responses at discrete times corresponding to smoke detector alarm levels. By comparing the means of the sensor outputs for fire events and nuisance source events, various signatures were identified as providing good discrimination between the events. The results of the analysis indicated CO_2 and

CO rate of rise signatures were important, indicating that a temporal analysis may reveal additional information of key signature patterns. The results also indicate that the measuring ionization chamber (MIC) and the ionization detectors provided good discrimination potential.

The report demonstrated the usefulness of multivariate methods for understanding the large fire/nuisance source databases. In particular, the methods were used to select candidate sensors to achieve the best classification results for a large number of real fires and nuisance sources. Correlation techniques and principle component analysis (PCA) were useful in identifying sensors that provide unique information for discriminating fire and nuisance source events. These analysis also indicated that the time aspect of the signature patterns (not just absolute sensor values) will be important in developing an effective multi-signature fire detector.

A Probabilistic Neural Network (PNN) that was developed at the Naval Research Laboratory for chemical sensor arrays was used to classify nonfire, fire and nuisance source events based on the time slice data corresponding to different smoke alarm levels. The multivariate analysis identified various sensor combinations that provided modest improvements in overall performance compared to the conventional ionization and photoelectric smoke detectors. Although selection of the appropriate sensor sets can be guided by multivariate analysis, the final decision must include practical assessments such as the availability of sensors, reliability and long-term stability. Discussions were presented of the potential limitations of developing detection systems based on experimental output from sensors. Ultimately, these discussions point to the need for an iterative process of analysis and prototype testing. Based on the results of this study, the following sensor combinations are recommended for consideration:

CO, NO, RION and ODM
CO_2, O_2, CO, ODM and RION
CO, MICX, RION and ODM

The results indicate that the primary products of combustion (CO_2, O_2, CO) and smoke are the key signatures. Nitrogen oxide (NO) is the only identified signature that is not a primary product of combustion. The results also reveal that the design of instrumentation used for measuring particulate (e.g., smoke detectors) is important. This is evidenced by the fact that both the MIC and the residential ionization detector (RION) are indicated as providing valuable information for discrimination (i.e., the data is not redundant) and the commercial ionization detector (Simplex) was not highly correlated to either the MIC or RION. It is also noteworthy that the optical density meter (ODM) was not highly correlated to the photoelectric detector. The ODM detects particulate by measuring the obscuration of a light beam as particles traverse the light path. The photoelectric detector detects particulate by measuring the amount of scattered light from particulate material entering a light path. The results of the multivariate analysis indicate that a smoke sensor for measuring low number density particulate should be based on light obscuration. Others, such as Pfister [21], have reported that better discrimination between fire and nuisance sources can be achieved by varying the design of ionization detectors so that different ion chamber voltages can be used. The work by Pfister is discussed in Reference 1. It

is concluded that a better understanding of smoke detector technology and particulate properties (e.g., size, size distribution, color and optical properties) will be needed in designing the prototype multi-signature fire detectors.

The three sensor combinations identified above when used with the PNN resulted in improved discrimination and fire detection capabilities than was achieved with the conventional ionization and photoelectric smoke detectors. Future work will focus on the temporal features of sensors. It is expected that the overall classification results will improve, and sensors that measure rapidly changing features such as oxygen, temperature and carbon dioxide may become increasingly important. The results of the multivariate Part I analysis indicate the significance of the temporal signatures and identified oxygen as a key signature. Where as, the results of Part II, which are based on discrete time data, did not indicate oxygen as significant. It is important to investigate the temporal effects of the sensors because a fire detection system will be functioning in a dynamically changing environment where these features will be prominent. This study provides a first step in the development of a sensor array for fire detection. Combinations of the sensors studied can provide improved performance over the current state-of-the-art. In addition, this study is the benchmark to compare discrete methods with temporal approaches.

8.0 RECOMMENDATIONS

The results of this study lead to the following recommendations:

1. The use of multiple signatures in a fire detection algorithm result in improved fire detection performance and reduction of nuisance alarms compared to conventional ionization and photoelectric smoke detectors.

2. Based on the multivariate analysis using the PNN, it is recommended that a multi-signature fire detector incorporate smoke sensors and sensors of combustion significance (CO, CO_2 and O_2). Nitrogen oxide was also identified as a potential candidate signature.

3. The results of the multivariate analyses has indicated that the design of smoke (i.e., particulate) sensors is key to developing an effective multi-signature fire detector.

4. A temporal analysis of the fire and nuisance source test data should be conducted to identify important transient signature patterns. This work will be conducted by the Environmental and Sensor Chemistry Section of NRL (Code 6116).

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